A MULTIVARIATE ANALYSIS OF FINANCIAL CHARACTERISTICS OF ACQUIRED FIRMS IN INDUSTRIAL MERGERS

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ABSTRACT

A MULTIVARIATE ANALYSIS OF FINANCIAL CHARACTERISTICS OF ACQUIRED FIRMS IN INDUSTRIAL MERGERS

by

Donald L. Stevens

The growth of one firm by the acquisition of another firm has seen increasing importance in the last decade. Although this external investment decision is not unlike the widely treated internal investment decision in the capital budgeting model, little attention has been paid to similarities between these two decisions to expand.

Most of the current research in the area of mergers has been directed at post-merger performance of merger-active firms, effects of mergers upon competition, and determinants of exchange ratios in mergers. This study is directed at the acquired firm and analyzes the financial characteristics of acquired firms for the two year period immediately prior to acquisition. Hypotheses are formulated as to systematic differences between acquired firms and similar firms which were not acquired. The differences analyzed are financial in nature and relate to the financial variables which are also relevant in the traditional capital budgeting framework.

Two samples of industrial firms were taken, each of size 40. The first contained firms acquired during 1966, and the second contained firms available in 1966 but not acquired as of 1970. For each of the firms, financial statement data was collected and a series of ratios were calculated to measure financial variables such as liquidity, profitability, leverage, and activity.

In that a great deal of multi-collinearity existed in the data, factor analysis was employed to reduce the ratio set to less than ten potentially useful variables which summarized the total data set and were mutually uncorrelated. These variables were used as inputs for multiple discriminant analysis (MDA). The MDA determined which set of variables best discriminated between the two samples, the relative contribution of each variable to total discrimination, and the significance of the differences between the groups on all of the employed variables.

The results of the initial MDA and the classification accuracy of the model were significant and indicated that acquired and non-acquired firms were different with respect to these financial variables. However, the evaluation of the assumptions of the MDA model resulted in a reformulation of the samples using an "attractiveness for acquisition"

criterion rather than the acquired and non-acquired groupings. Factor analysis was employed again to re-align the firms into those mutually exclusive sample groups. MDA was then used and results were very significant at all stages of the analysis. For both models the attractive-acquired firm samples were more profitable, more liquid, had higher asset turnover, and much lower levels of debt. For the natural groups model, dividend payout also entered the discriminant function and attractive firms had higher dividend payout. The discriminant model was validated by accurately classifying firms not used in the development of the model. These findings were consistent with the belief that a financial basis was common to the merger decision similar to that of other asset acquisition decisions.

This study also demonstrated the usefulness of a multivariate framework in financial analysis. Empirical research of this kind often faces the problem of multicollinearity and factor analysis was shown to be a useful device to summarize the total data set without significant loss of information, such that the remaining variables minimized the inter-correlation problem. MDA proved to be a useful technique for detecting group differences and indicating which variables best distinquished the groups. This

application of these tools should provide incentive for their future application in research in finance.

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CHAPTER I

INTRODUCTION

A firm seeking to expand has two avenues for growth. The first is internal growth which involves the acquisition of economic resources which are transformed into goods and services within the existing firm. The second is external growth by the acquisition of the assets of existing entities by means of merger.

Although both alternatives should lead to the same ultimate goal--maximization of the wealth of the firm's owners--the two methods have been treated quite differently by both the business and regulatory communities, and by academicians in economics and finance. Specifically, the area of capital budgeting decision making has been directed at evolving a theory which sets forth the principles for evaluating alternative asset acquisition decisions. Numerous financial criteria are developed for inputs into models designed to measure risk/return relationships and lead to a decision. While both types of growth, external and internal, would intuitively be included in a capital budgeting framework, the direction and emphasis in capital budgeting has

been only with the internal growth of a firm and the investment decisions surrounding that problem.

The acquisition of assets may be for any number of purposes within the firm. Marketing, production, and physical distribution projects all compete for limited funds available to the firm at any point in time. The competition of the many projects is evaluated using the capital budgeting framework, and based on a measure of risk and flows of benefits from the projects. Thus, independent of the specific qualitative benefit of a proposal, such as a more efficient production assembly process versus a faster inventory control network, the capital budgeting framework transforms the benefits so that they can be evaluated in terms of expected cash benefits from the project. Therefore, projects don't compete on qualitative measures such as "more efficient" and "faster", but rather on the increment of wealth gained from their acceptance. The wealth increment is measured by the present value of expected cash benefits from a project.

However, if one were to review the existing merger literature in finance and economics, it would appear that other motives and reasons dominate the decision to grow externally through merger. Little attention has been given to a search for systematic similarities which may

exist to subject the external growth decision to the same capital budgeting framework as an internal growth decision. No doubt, the going concern has many additional dimensions which need identifying as part of the investment decision process, but the premise remains that all investment decisions implemented with the traditional capital budgeting framework, evaluate financial variables in terms of present values and risk. The merger decision may add new criteria to this framework, or attach different weights to the same criteria, but the merger decision remains an investment decision which can be accepted only if the result is an increase in the value of the firm to it's owners.

PURPOSE OF THE DISSERTATION

The research investigates two areas. First, the relationship between financial profiles of industrial firms and likelihood of acquisition, and the applicability and usefulness of financial ratios and ratios analysis to the measurement of performance and development of financial profiles. Second, the statistical tools of factor analysis and multiple discriminant analysis (MDA) will be employed to financial analysis as analytical substitutes for traditional, judgemental methods.

The investigation of the first question will proceed with the hope that extensions to the current state of

knowledge will accrue in that merger research has not taken this particular approach at this point in time. Although much interest exists as to why firms merge and the economic significance and implication of mergers, the great share of empirical testing has been conducted with respect to either the merger transaction itself of with post-merger performance. The second area of investigation, multivariate analysis techniques as tools in this context, will extend and serve as a replication of other successful research using these methods in finance and related disciplines.

OUTLINE OF THE DISSERTATION

Chapter II will evaluate the direction taken in merger research in recent years. This includes the views of the business community, the direction of regulatory studies, and the emphasis in academic research. From this body of research the specific efforts relating financial criteria to any phase of the merger decision will be discussed. This will be used to formulate, where possible, hypotheses pertaining to a priori belief about financial qualities and their relation to acquisition. Where there is no consistent belief, both sides of the issue will be discussed.

Chapter III reports the research design by which the hypotheses are examined and tested. The nature of the

firm samples and the type of data collected are described. The tool of factor analysis is introduced for the purpose of simplifying the large set of original data. This reduced set provides the basis for the actual testing for differences between samples which is performed in Chapter IV.

Chapter IV uses multiple discriminant analysis to analyze if financial differences exist between acquired and non-acquired firms. Further, it determines, in the case of differences, which financial variables are most different between the groups. Assumptions of the MDA are examined and the reformulation of the samples leads to further insight about financial characteristics and attractiveness for merger.

Chapter V reviews the results of the tests with respect to the hypotheses of Chapter II, and draws conclusions about differences between the samples. Further, the usefulness of the multivariate techniques is evaluated and limitations of the study are discussed. Finally, suggestions for future inquiry are made for using these findings in the area of mergers and for the future applications of the multivariate tools in financial research.

CHAPTER II

MERGER RESEARCH AND FINANCIAL CHARACTERISTICS OF FIRMS

INTRODUCTION

This chapter reviews the areas of investigation in merger research which relate both to the current merger movement and to this research. Merger research has taken many directions in the last decade within the fields of economics and finance. The existing literature in these areas contains numerous attempts to explain various facets of the merger movement as well as effects of mergers.

There may be as many reasons for the acquisition of one firm by another, as there have been mergers. No doubt, there are unique reasons in every merger which contribute to the decision to acquire or to be acquired. In most cases, however, while the relative importance of these unique reasons in a single merger may be noteworthy, they are not likely to be significant to the merger movement as a whole. However, if reasons and goals do exist which are common to most mergers, learning these goals and reasons would contribute a great deal to the understanding of the

merger movement.

DIRECTIONS OF MERGER RESEARCH

There have been a number of attempts to analyze the corporate merger and what role the merger plays in the growth of a firm. Two of these, quite different in scope, were the Federal Trade Commission's Economic Report on Corporate Mergers,[1] published in 1969, and The Corporate Merger, by Alberts and Segall.[2] The latter contains a series of papers presented at a seminar in 1963 by both professional and academic participants, all experienced and knowledgeable in various aspects of mergers.

The emphasis of the FTC study was a concern about increasing levels of economic concentration in a relatively few large corporations, and an evaluation of the competitive consequences of the increased concentration. The merger study was in that context and the role of the merger in increasing economic concentration was emphasized.

One section of the FTC study discussed the factors encouraging the current merger movement. A number of

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[1]Federal Trade Commission, Economic Report on Corporate Mergers, Hearings on Antitrust and Monopoly, Committee of the Judiciary, U.S. Senate, 91st Congress, 1st session; Part 8A, USGPP, 1969.

[2]Alberts, W. W. and Segall, J. E. The Corporate Merger, Chicago: University of Chicago Press (1966).

incentives to grow through merger were identified including market power, efficiencies of various types, economies of scale, and specific tax and accounting advantages. A conclusion of this section of the study points out the FTC concern.

> The balance of evidence so far available lends little support to the view that the current merger movement reflects, in substantial measure, efforts to exploit opportunities to improve efficiency in resource allocation. On the contrary, there are abundant indications that certain institutional arrangements involving tax and accounting methods, aided by speculative developments in the stock market, have played a major role in fueling the current merger movement. In this context there is little reason to expect significant social benefits to flow from a continuation of current trends. Further reasons for concluding that current merger activity, particularly insofar as leading firms are involved, represents a divergence between private and social benefits are developed in subsequent chapters.[1]

Resultant recommendations centered around more vigorous enforcement of anti-trust statutes, more complete disclosure of financial operations of major corporations, and tax reform to eliminate tax incentives for merger.

It would be easy to conclude from the FTC report that the merger movement was dominated by a few giant firms devouring the most profitable and efficient of the competitors in numerous industries.

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[1] FTC, op. cit., 159.

While the FTC report points out the concern of that regulatory body of the role of the merger in increasing concentration of assets into the control of a few large companies, these mergers do not dominate the merger movement. The same FTC report estimated that over 15,400 mergers were consummated during the period 1948-1968, and only 1,276 of these involved acquired firms with assets in excess of $10 million at the time of acquisition.[1] The question remains as to what motivations cause firms to seek out other firms for acquisition, when the parties to the mergers are not giants in their respective industries.

The discussion and analysis of numerous aspects of the merger decision was the direction taken in The Corporate Merger. Advantages and dis-advantages of external growth by merger and internal growth were analyzed. Sources of gain through merger were discussed and each phase of the merger transaction received attention.

In a concluding and summarizing paper, Alberts attempted to assimilate the thoughts of the other participants. Merger gains could be expected, he concluded, only in the presence of synergy and operating economies without relaxing the assumptions of efficient pricing and valuation

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[1]FTC, op. cit., Table 1-1, 43; and Appendix Table 1-3, 667.

of the respective firms in the merger. However, if the possibility of "bargains" prices is introduced, additional sources of gain arise.

The measure of the importance of potential bargains is that they should be relatively common, be detectable by merger active firms, and be exploitable. After examining numerous potential bargain sources and measuring these against the above criteria, Alberts reduced the bargain set to the following group: 1) tax bargains; 2) mis-management bargains; 3) cost-of-capital bargains; and, 4) forecast bargains.

Tax bargains provided opportunity due to tax statutes which allowed gains upon merger in certain circumstances. This was also noted by the FTC study. Mis-management bargains existed in those firms which were operated at less than maximum efficiency, and upon acquisition, the improved management could increase the value of the combined firm. The cost-of-capital bargain existed where the market systematically applied different capitalization rates to certain classes of firms. Thus, upon acquisition, the realignment of the capitalization rate would increase total combined value. Forecast bargains occurred when the acquisition was made of a firm whose owners had been overly bearish in their estimates of the future performance of the firm

and had undervalued the stock.

The mis-management bargains notion has been directly discussed by some authors and implied by others indirectly. Manne[1] argued that mis-management bargains were common and many mergers were made to exploit them. Additional exploration of the mis-management bargain idea will be developed later in this chapter.

The cost-of-capital bargain is dependent upon discrepancies in the market valuation mechanism. If small firms are systematically capitalized at a higher rate than are large firms, large firms could acquire small firms generally and achieve higher total value of the combined firm. In addition, for firms who are small and have infrequent access to the capital markets and do not have active secondary markets for their common stock, the lack of "marketability" would give ample opportunity for cost-of-capital bargains. The forecast bargain, noted by Alberts, would relate to this situation also. If the management of a firm and/or the market, is inaccurate in its forecast of the future performance of a firm, then another firm that could detect this and accurately revalue the firm, could

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[1]Manne, Henry, G. "Mergers and the Market for Corporate Control," Journal of Political Economy, LXIII (April, 1965), 110-120.

realize a gain.

The existance of gain in the case of market valuation discrepancies was explored by Gort.[1] He believed that economic disturbances such as new growth and technological change, resulted in basic changes in the firm causing valuation problems. The past for the changed firm is no longer a good indication of the future and the result would be greater dispersion in the market valuation of the firm. The discrepancies allowed for gains by the acquisition of those firms. While this would, no doubt, account for some of the mergers in the current merger movement, it is not at all likely that the movement could be generally accounted for by this phenomenon. Lewellen observed that "valuation errors of the scale and frequency required to explain much of the level of conglomerate activity in the 1960's would connote a degree of market imperfection, or a pattern of investor perversity, that most investigators nowadays would be unwilling to grant."[2] Such is the case with most of the individual explanations of why firms merge. Other authors

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[1]Gort, Michael. "An Economic Disturbance Theory of Mergers," The Quarterly Journal of Economics, LXXXIII (November, 1969) 624-642.

[2]Lewellen, Wilbur G. "A Pure Financial Rationale for the Conglomerate Merger," The Journal of Finance, XXVI (May, 1971) 521-537.

have also enumerated the same items in different form.[1] Joel Dean listed the same basic traits as characteristics which make a company a tempting target for takeover.[2]

MERGERS AND FINANCIAL CHARACTERISTICS

While the explanation of why firms merge in particular situations are numerous, and many kinds of explanations are offered for incentives to merge, little has been achieved in reducing these to one or a few criteria which would hold for the majority of mergers. To this end, an obvious point of departure would be the standard theory of the firm framework. If one assumes firms make decisions to maximize the wealth of their owners, merger decisions must compete with other investment decisions before the firm. These would include at any point in time, both internal investment alternatives and other merger alternatives. When a merger path is chosen, the benefits from the merger must have been recognized as being superior to the other alternatives. In the capital budgeting framework, the future expected benefits from the acquisitions (whether

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[1] Conglomerate Mergers and Acquisitions: Opinions and Analysis, 44 St. Johns Law Review (Special Edition, 1970).

[2] Dean, Joel S. "Causes and Consequences of Growth by Conglomerate Merger: An Introduction," Conglomerate Mergers and Acquisitions: Opinion and Analysis, 44 St. John's Law Review, (Special Edition, 1970).

they are the result of operating efficiencies, marketing advantages, or some other reason) as estimated by future cash flows, must have greater expected present value.

If this is the case, the investigation of the characteristics of the acquired firms themselves and the acceptance of the capital budgeting framework for decision making would allow a technique whereby the possible gains from merger might be reflected.

The following section reviews additional research with the goal of relating mergers to this criterion of potential gains from a merger being reflected in the financial flows and criteria of the acquired firm. This development will be the primary emphasis of the dissertation. The existing research will be used to develop a set of criteria of financial characteristics of acquired firms which either directly measure potential gain from merger, or indirectly reflect gains. The research will be discussed in a section on merger transaction studies and a section on financial criterion studies.

Merger transaction studies have analyzed the relationship between financial variables of the parties to the merger and the exchange ratio in stock exchanges. Also, the use of various other financial instruments has been studied with respect to the post-merger earnings effects

from different financing methods.

Dellenbarger used multiple regression techniques to study the determinants of exchange ratios in industrial mergers.[1] He concluded that earnings per share, cash dividends per share, book value per share, and market price per share of the firm's stock were the relevant variables between the firms in the determination of the actual exchange ratio.

Another type of merger transaction study was that of Pinches, who studied the effect of convertible preferred stock as a financing instrument in mergers.[2] He tested to see if this instrument altered the post-merger earnings of the combined enterprise, and resulted in higher earnings than if other financing methods had been used. He was unable to reject a null hypothesis although differences were observed in the direction in which he would have predicted. However, he did note in separate testing, that market prices and earnings of merging firms were the dominant factors in exchange ratios.

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[1] Dellenbarger, Lynn, E. Jr. Common Stock Valuation in Industrial Mergers, Gainesville: University of Florida Press, 1966.

[2] Pinches, George E. "Financing Corporate Mergers and Acquisitions with Convertible Preferred Stock," Unpublished Ph.D. Dissertation, Michigan State University, 1968.

Previous studies by Bosland,[1] Weston and Brigham,[2] and Reilly,[3] also evaluated determinants of exchange ratios with similar variables taking on importance in the respective works. Weston and Brigham did, however, emphasize that unique circumstances of individual mergers often dominated other variables.

The research question raised by these studies is as follows: If financial qualities such as profitability, dividend policy and price/earnings ratios are the dominant decision variables in the merger transaction, do they serve a similar role in the search for acquisition candidates? To the extent that they do, certain types of firms should emerge as favored over other firms due to their profiles on these variables.

The financial criterion studies have been attempts to relate merger motives generally to a financial bases.

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[1]Bosland, Chelcie. "Stock Valuation in Recent Mergers: A Study of Appraisal Factors," Trusts and Estates (June, July and August, 1955) 516-669.

[2]Weston, J. Fred, and Brigham, Eugene F. Managerial Finance, 2nd Edition, New York: Holt, Rinehart & Winston, Inc. (1966) 661-682.

[3]Reilly, Frank K. "What Determines the Ratio of Exchange in Corporate Mergers," Financial Analysts Journal, XVIII (Nov., Dec. 1962) 47-50.

Lintner[1] analyzed the post-1950 merger movement and contrasted its characteristics with the merger waves of earlier periods. He identified opportunities for gain by merger due to 1) reductions in lenders' risk of bankruptcy losses; 2) scale diseconomies in credit investigation of smaller firms, in floatation expenses in public issues and in investor information (marketability); and, 3) changes in investors' assessments of future prospects per share when price/earnings ratios differ.

With respect to the leverage gains Lintner notes that even if the merging firms have optimal capital structure, two sources of gain exist through leverage. First, borrowing costs decline as firm size increases and, second, reduced lenders' risk increases debt capacity. Because the earnings streams of the merging firms are not generally perfectly correlated, the joint probability of failure in any period is less than the sum of the separate probabilities for the firms independently.

Levy and Sarnat also noted this and further pointed out that limits exist to the diversification effect, and, to the extent that firms become very large and well

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[1] Lintner, John. "Expectations, Mergers and Equilibrium in Purely Competitive Securities Markets," American Economic Review, LXI, No. 2 (May 1971) 109-114.

diversified, financial risk may become insignificant.[1]

Lewellen addressed this same question of "whether it is possible for firms, by merging, to produce gains for their stockholders in the absence of any opportunities for operating efficiencies--to create increments in wealth out of 'pure' financial combination of enterprises."[2] If the possibility exists then when other sources of gain also are present due to increased efficiency and better management, the merger will be that much more desirable to the firm's shareholders.

Lewellen's argument for the purely financial rationale for merger is that the increased size of the combined enterprise and the lower joint probability of failure increases debt capacity and lowers lenders' risk. This accrues independent of any increased debt capacity of the individual firms. Thus, market value increases in the combined firm are obtainable even in the absence of market imperfection.

These authors jointly establish financial rationale for mergers and the increased debt capacity, lower lender

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[1]Levy, Hiam and Sarnat, Marshall. "Diversification, Portfolio Analysis and the Uneasy Case for Conglomerate Mergers," The Journal of Finance, XXV, No. 4 (Sept. 1970), p. 801.

[2]Lewellen, op. cit., 522.

risk benefits of mergers, are operative even in the case of optimal capital structure of the merging firms. Other possibilities can be generalized from their contributions in the case of less than optimal capital structures. First, in the case of an acquiring firm with excess debt, the merger would lower financial risk and move the new firm in the direction of an optimal capital structure. Second, in the case of the acquired firm with little or no debt in its capital structure, considerable debt capacity is gained. First the unused portion of debt capacity of the acquired firm independently is available, plus the additional capacity from the combination of the firms.

Therefore, debt capacity and capital structure should be an important financial variable when searching for merger targets. Even if it is accepted that gains accrue with optimal capital structures, to the extent that acquired firms tend to be conservative employers of financial leverage, they should be more attractive.

A similar line of argument can be advanced for the case of firms with less than optimal levels of current assets. Gains from acquisition of firms of this type could arise independent of earnings expectations. The acquiring firm, by reducing the excess levels of the overly liquid acquired firm, would gain a one-time release of funds

which could be subsequently reinvested. This type of gain would be the result of a mis-management bargain of the type described by Manne.[1] The cash benefits from this process would be immediate and relatively risk free, compared to cash benefits from typical capital budgeting projects of the firm. The present value of these funds would be their capitalized value, using the firm's cost of capital as the capitalization rate.

The concept of excess liquidity and attractiveness is much more apparent in the business community, than the debt capacity arguments. A number of sources are available which give collective insight into how management of merger active firms searches and screens acquisition candidates.[2] Interesting insight into the acquisition process was provided by Hutchinson,[3] who edited a series of presentations

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[1]Manne, op. cit., 110-120.

[2]Hutchinson, G. Scott (ed.) The Business of Acquisitions and Mergers. New York: Presidents Publishing House, Inc., 1968.

Mace, Myles L., and Montgomery, George G., Jr. Management Problems of Corporate Acquisitions. Boston: Graduate School of Business Administration, Harvard University, 1962.

McCarthy, George D. Acquisitions and Mergers. New York: Roland Press, 1963.

Short, Robert A. Business Mergers: How and When to Transact Them. Englewood Cliffs: Prentice-Hall, 1967.

[3]Hutchinson, op. cit.

by executives active in acquisition programs. Most firms used similar criteria in searching for acquisition candidates. Important financial criteria included expectations of earnings, growth, and rate of return on assets. Generally, these were established with reference to the performance of the acquiring firm itself. The role of liquidity was consistently stressed as an important criterion in the eyes of the acquisition executive. "In my opinion, the most important thing to do in reflecting on an acquisition is to study the history in terms of cash flows."[1] And, by another executive: "...the determining factor in the success of all subsequent deals has been the effective nonuse of cash."[2] In fact, liquidity oriented methods such as payback and cash recovery period were often used to evaluate the proposed acquisition.

SUMMARY AND STATEMENT OF RESEARCH QUESTIONS

All of the preceding studies suggest a diversity in belief and illustrate the lack of a consistent and cohesive collection of thoughts for testing with empirical data. There were, of course, conclusions drawn from all of the studies, but no attempt to assimilate. The process of

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[1]Hutchinson, op. cit., p. 181.

[2]Hutchinson, op. cit., p. 232.

assimilation raised questions as to if there existed systematic differences between firms chosen for acquisition and those discarded.

In a capital budgeting sense, an acquisition will take place if the present value of the expected benefits is greater than the present value of the expected outlays. Thus, even if the primary motive for an acquisition does not appear to be financial, it must ultimately be weighed for its financial impact upon the stockholders' wealth in the combined enterprise. The success of all investment decisions must be measured for the effect upon the value of the firm.

However, the existing empirical research, with emphasis upon the performance of merger active firms, and post-merger performance has not been able to deal with pre-merger conditions which would have motivated the merger over some other alternative. Certainly each merger decision was weighed against alternatives which would include the acquired firm against other potential firms which were acquisition candidates at that point in time. An important question not answered in the current literature is what qualities existed in the acquired firm which resulted in their selection over other similar firms?

The actual target firms should exhibit measureable

differences in order to attract acquisition minded firms. If these are directly measureable financial qualities or even indirectly measureable qualities which are reflected in a firm's financial posture, then an analytical framework may be possible to attempt to isolate the differences.

With this framework, it may be possible to discover the differences and make judgments or formulate new hypotheses pertaining to why firms merge. It may be that differences between firms which could lead to merger of one and not the other are differences unique only to the two firms involved and could not be detected by analysis not recognizing the unique conditions. No doubt, mergers do occur for reasons unique to the merging parties but, the frequency of transactions of this type should be small.

In the section which follows, an attempt will be made to assimilate both rationale for merger and the financial qualities which may possibly reflect conditions attracting merger initiatives. These financial qualities will be used as the primary independent variables to test for differences between firms acquired and firms not acquired at a point in time. The implied null hypotheses which will be tested are that, for each of the financial qualities or variables, no differences exist between acquired and non-acquired firms. The rejection of these

null hypotheses would allow conclusions to be drawn as to the specific differences between these firms, and would be the basis for the formulation of new hypotheses concerning the types of variables which are most systematically different in firms which are acquired. This would allow definite insights as to which of the motives for merger enumerated in the literature are actually found in practice.

Each of the financial qualities or variables will be stated and discussed as to how acquired firms would be expected to differ from non-acquired firms on this variable.

LIQUIDITY: To the extent that mis-management bargains occur, as discussed by both Alberts and Manne, acquired firms should be more liquid than non-acquired firms. Liquid assets are easily transferred to the acquiring firm which may need liquidity for current operations and/or additional acquisitions. Excessively high levels of liquid assets indicate, generally, inefficient management of assets or lack of investment opportunities.

FINANCIAL LEVERAGE: Acquired firms should have lower levels of debt than their non-acquired counterparts. This adds to the attractiveness of a firm in that not only is an increment of debt capacity added from the increased size of the combined firms, but also the unused debt capacity of the acquired firm will further add to the borrowing capability

of the merged firm. Additionally, the conservative management which allows high levels of liquidity and other inefficiencies to occur, would, predictably, not be aggressive users of financial leverage.

ACTIVITY & TURNOVER: This is another measure of efficiency type qualities in a firm in that the more efficient a firm's management operates, the greater the turnover of assets. If firms were conservative and mis-managed levels of liquidity and leverage, turnover would be expected to be lower than aggressive firms.

PROFITABILITY: In a univariate sense, it is difficult to make a priori statements about the profitability of acquired firms. If they are conservative or mis-managed, profits may still be satisfactory, but not as large as they would be with better management. Arguments exist which would allow prediction either way. The FTC implied that acquired firms were the most profitable in their respective industries, but bargains would be expected to occur more frequently with conservative firms who were undervalued by investors.

DIVIDEND POLICY: Again, dividend payout ratios by themselves could be predicted to be either higher or lower by current theory. It would be expected to correlate highly with other financial qualities of the firm. For example, a highly liquid firm, with low levels of debt, and

conservative management would be expected to pay good dividends. Thus, high dividend payout and acquired firms could aling with one another. However, if mergers occur from stockholder dis-satisfaction, low dividend payout would be a good indicator of stockholder dis-satisfaction, along with poor earnings. Thus, as in the case of the profitability factor, the univariate information content of these qualities is low, whereas their joint behavior with other qualities could be very enlightening.

PRICE/EARNINGS RATIO: This ratio will be a good measure of the cost-of-capital bargain potential which exists according to Alberts, et al. If the market systematically undervalues small firms, or certain other types of firms, and undervaluation can be reflected in low PE ratios, then these firms will be acquired in order to benefit from the market adjustment. In this context acquired firms would be expected to have lower price earnings ratios than non-acquired firms.

SUBSEQUENT ANALYSIS

The next section, translates the research questions and hypotheses into a form for formal analysis of differences. Financial qualities such as those listed above, will be measured by alternative ratios and these will be used to develop a formal framework for the analysis of differences between the acquired firms and non-acquired

firms. Finally, conclusions will be drawn with respect to these hypothesized differences.

CHAPTER III

SAMPLE DESIGN, DATA ANALYSIS AND FACTOR ANALYSIS

INTRODUCTION

The process of gathering and transforming the data into a form suitable for analysis involved a series of compromises between theoretical rigor to minimize sampling and non-sampling error, and unavoidable reality always encountered in empirical research.

In this chapter the data and ratio analysis sections report the sampling of firms and development of financial qualities hypothesized to be different between the samples. The remaining sections introduce factor analysis as an analytical technique for data simplification. First, the technique is developed and described, followed by the actual employment of the tool with the data. The two related multivariate studies (Altman, and Monroe and Simkowitz) relied upon vaguely specified judgemental procedures in reducing the input ratios to a much smaller set for the final discriminant model. The use of factor analytic procedures in this study represented an attempt to improve and extend the

contributions of these researchers' methodologies within the multivariate context.

DATA

A primary problem in any research involving mergers and financial information for firms which have been acquired, is that of accurate reasonably complete data. Especially in the case of acquired firms, data is available in only a few cases and is often not complete. Reid, in his book Mergers, Managers and the Economy, noted the limited research on mergers reported in the literature.[1] The data problem may explain the limited inquiry with respect to the characteristics of acquired firms. Reid notes: "We do not know the pertinent financial data about most of the acquired firms, such as assets, market price of stock (if traded), profits, and sales volume."[2]

The data source for listings of firms involved in mergers was the Federal Trade Commission's Bureau of Economics. The FTC annually publishes a listing, Large Mergers in Manufacturing and Mining, containing names of acquiring and acquired firms in mergers beginning with

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[1]Samuel Richardson Reid, Mergers, Managers and the Economy, New York: McGraw-Hill Book Co. (1968) 20.

[2]Reid, op. cit. 21.

1948.[1] Additionally, date of acquisition, asset value and type of merger, are listed. Large mergers were defined as those with asset size at the time of acquisition of no less than $10 million. The deficiencies of the FTC data are well documented in most of the existing empirical research on mergers.[2] The primary problem is the extent of coverage. Mergers involving small firms are not recorded with any great frequency, and even the listings of large mergers are not totally comprehensive. The FTC estimated that its listing of large acquisitions included 70.0% of all mergers in the $10.0 million and above asset class. However, in response to an inquiry for listings of mergers involving firms with less than $10 million of assets, the FTC estimated their coverage for the smaller classes would be only about 10% of the total number of mergers. The principal data sources used by the FTC are Moody's Industrials, Standard & Poor's Corporation Records, The Wall Street Journal, and other newspapers and prospectuses filed with the Securities and Exchange Commission.[3]

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[1]Federal Trade Commission, Large Mergers in Manufacturing and Mining 1948-1969, Statistical Report #5, Bureau of Economics, March 1970.

[2]Gort, op. cit., 632; Pinches, op. cit., 48; Reid, op. cit., 20-21.

[3]Federal Trade Commission, Large Mergers, op. cit., 2.

In consideration of these data deficiencies, and the nonexistence of alternative data sources, the scope of the study was limited to industrial firms with assets of at least $10 million at the time of acquisition.

Another problem was discovered in developing the sample of acquired firms. Firms which were included in the FTC listing did not always have complete financial statement data available in Moody's manuals. Moody's was used as the source of balance sheet and income statement data for both samples. In the cases where required data was not complete, the firm was deleted from the sample. Of the original listing of 69 firms by the FTC for the sample year, 40 were found with complete data, and these firms composed the sample of acquired firms.

The design of the second sample, that of firms which had not been acquired, was a stratified random sample of industrial firms. The stratification was with respect to the size distribution of assets, and was made with the intention of having two samples of firms with the same relative distribution of firms by size of assets. The logic behind this decision was that there is a relationship between the size of a firm and its likelihood of being acquired. For example, firms with asset sizes in excess of $250 million are much more susceptible to Justice

Department antitrust action to block the merger than are small firms.[1]

The same data availability requirements were imposed upon the second sample. The following criteria were met by the 40 firms included in the second sample:

1. The firm was in existence in 1966 (the sample year) and had not been acquired subsequent to that year, and as of January 1, 1970.
2. The firm had financial data available in Moody's for the years 1961-1966 (the test period).
3. The firm had assets valued at no less than $10 million in 1966.
4. The firm was listed on either the New York Stock Exchange or the American Stock Exchange.

The first criteria assured that firms in the second sample were in existence and "available" as candidates during the sample year. The second and third criteria were the same as those met by the first sample.

The decision to require firms in the second sample to be listed firms was made to attempt to eliminate some of the firms which may have been attractive merger targets but unavailable for acquisition because they were closely held

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[1]FTC, Economic Report on Concentration, op. cit., 13.

and the majority stockholders did not want to merge. While it is recognized that listed firms exist which have small groups of stockholders which constitute a majority of the voting stock, it was felt that a sample of listed firms would be less likely to include these firms. To the extent that firms of this type were included in the second sample, this would decrease the discriminating ability of the model. As a further precaution, during the data collection, if information was available with respect to "large" stockholders, this was used to exclude the firm. In these cases, if a firm had one or a small number of stockholders who owned more than 20% of the voting stock, the firm was excluded. The 20% cut-off was arbitrary but made with the belief that substantially less than 50% of the voting stock was needed to control a firm which meets listing requirements, because many stockholders never exercise their voting rights.

The selection of 1966 as the test year was based on several factors and represented a compromise. First, a recent year was desired for the test year in order to give as much relevance to the results as possible. However, in order to establish that firms in the second sample were not about to be acquired, it was felt that there should be a time interval subsequent to the test year to observe whether

any firms in the second sample had been acquired. Another restriction existed because much of the FTC information for the most recent years was preliminary. Finally, years earlier than 1966 were ruled out because of the small number of mergers listed by the FTC.

The 1961-1966 test period was also chosen after consideration of several criteria. Of primary importance was that the test period should immediately precede the acquisition, as this period would be used by acquiring firms in their analysis and valuation of merger candidates. When evaluating the level of borrowing of an acquisition candidate, for example, the relevant data is the current level of outstanding liabilities, not the twenty year history of borrowing. The five year period was chosen to assure the collection of enough data to assure flexibility with respect to the data and its measurement by ratios, some of which are subject to extreme values. Also a five year period would facilitate initial screening of the data for errors in collection and translation to analytic form.

To summarize, the original sample consisted of two groups of 40 firms, one group of firms acquired in industrial mergers, and a second group which had not been acquired. The test year was 1966 and balance sheet and income statement data were collected for the 1961-1966

test period.

RATIO ANALYSIS

The role of traditional ratio analysis in the area of finance is well known and the wide use of ratios as a tool for analysis in numerous contexts needs no review here. It is equally apparent that "traditional" ratio analysis has lost its place as a tool for analysis, and has been replaced in the current literature by more analytically oriented methodologies using statistical techniques as the basis for models and hypothesis testing.[1] Academic research efforts, with the assistance of the computer, have turned to more powerful tools for measurement and testing. Altman re-introduced ratio analysis in a multivariate context and developed a discriminant model with respect to likelihood of bankruptcy based upon a ratio profile.[2] The ability of the model to classify firms with over 90% accuracy up to three years prior to bankruptcy illustrates one instance in which the use of ratios with a statistical tool such as discriminant analysis, was very powerful.

The success of the Altman model prompted the use of

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[1]Edward I. Altman. "Financial Ratios, Discriminant Analysis and The Prediction of Corporate Bankruptcy," Journal of Finance (September 1968), 589-609.

[2]Ibid., 590-593.

a similar technique in this study. It was decided that financial ratios would be employed with both samples to measure various financial qualities. There exists an almost endless combination of financial data, any of which could be called a ratio. In order to reduce the set of available ratios for financial analysis, a search was made of the merger literature and the work of other researchers in related areas with similar tasks. Due to the number of significant ratios found to be useful in other studies, a list of 20 potentially helpful ratios was used. Ratios listed were classified into several classes. These classes were profitability, leverage (financial), liquidity, and activity. Table 3.1 is a summary of the ratios used, by class, in the final series of analyses. This group formed the data matrix which was factor analyzed. Other ratios chosen initially, or added during the analysis, were subsequently discarded dur to lack of complete and reliable data for all of the firms. For example, cash flow information for other than large firms was often not available in Moody's for the entire test period. In addition, during the analysis, ratios were deleted and changed in an attempt to find those which best measured the above financial qualities and were least subject to extreme variations. Table 3.2 contains pertinent statistics for the samples including means and standard

deviations for each of the ratios.

FACTOR ANALYSIS AS A MULTIVARIATE TOOL

The matrix of correlations among the ratios is presented in Table 3.3 and indicates the high level of collinearity among the variables. Research problems of this type typically face this situation at some stage. The problem was to choose a subset of the original group of ratios such that the ratios were not highly correlated among one another, and, at the same time, the subset contained as much of the information of the entire set as possible.

Such a problem can be solved with the use of factor analysis. Factor analysis is a powerful multivariate method which enables the researcher to simplify and summarize a large data matrix into a smaller one without appreciable loss of information. This technique is primarily concerned with the resolution of a set of observed variables with linear transformation, to form new derived variables (factors), and considerable parsimony, or simplification, is attained.

Kendall classifies statistical relationships into two categories; analysis of dependence and analysis of interdependence.[1] Analysis of dependence includes both

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[1]Kendall, M. G. "Factors Analysis as a Statistical Technique," Journal of the Royal Statistical Society, Vol. 12 (1950), 60-73.

TABLE 3.1

SUMMARY OF FINANCIAL RATIOS EMPLOYED

Class	Number	Ratio
Liquidity	12	net working capital/total assets
	18	net working capital/sales
Profitability	1	EBIT/total assets
	6	gross profit/sales
	7	EBT/sales
	8	net income/sales
	9	EBIT/sales
	10	net income/net stockholders equity
	11	net income/total assets
Leverage	4	long term debt/market value equity
	5	LT liabilities/mkt. value equity
	14	LT debt/net stockholders equity
	19	LT debt/total assets
	20	total liabilities/total assets
Activity	17	sales/total assets
	16	cost of goods sold/inventory
	15	sales/(current assets-inventory)
"Other"	13*	interest/(cash + marketable securities)
	2	cash dividends/net income
	3	price/earnings

NOTE: The distinction between LT debt and LT liabilities was that LT debt included only long term bonds and similar obligations whereas LT liabilities included all entries of a long term nature.

*This ratio behaves similarly to LIQ and LEV.

analysis of variance and regression analysis. These tools have had wide application in research in the area of finance in recent years. It has appeared to some that, in some cases, their use may have unduly limited the research in which they were used, as well as the conclusions drawn from these studies.[1] Within the last several years, however, other tools have been introduced into the literature which may prove to be equally as powerful and more applicable in many instances. These methods come under Kendall's classification of analysis on interdependence. This class includes various types of correlation analysis, cluster analysis, factor analysis, and multidimensional scaling. The important distinction between the two categories is that the techniques under analysis of dependence all require the designation of one or more of the total variables in the analysis as dependent variables. The techniques under analysis of interdependence focus attention on relationships among the total set of variables without singling out any of them for special consideration as dependent variables.[2]

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[1]Michael Keenan. "Models of Equity Valuation: The Great SERM Bubble," Journal of Finance, XXV (May, 1970), 244-260.

[2]Jagdish Sheth. "The Multivariate Revolution in Marketing Research," Journal of Marketing, Vol. 35 (Jan., 1971), 14.

FACTOR ANALYSIS IN THIS STUDY

Kendall's categories are relevant to the use of factor analysis in this study. The specific problem was a large number of intercorrelated ratios with information about a group of firms. The task was to reduce the number of variables without loss of information. The total set of variables was of the essence; no dependent variable existed in this context.

The principal aim of factor analysis is the principle of scientific parsimony[1]--a construct or a model should be simpler than the data upon which it is based--which will be illustrated in the following section in terms of the problem at hand.

Suppose we have a data matrix, X, of size 20x80, in which each element x_{ji} represents variable i's measurement of a quality on the j^{th} firm (i=1,2,3,...,n; N=80 and n=20 in this study). For any one of the characteristics x_j, the system $(x_{j1},x_{j2},x_{j3},\ldots,x_{jN})$ of N real numbers can be considered a point in N-dimensional space. However, by considering each system as a vector, we simplify the configuration to 20 dimensions, although these 20 dimensions must

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[1]Jagdish Sheth and Douglas Tigert, "Factor Analysis in Marketing," unpublished paper presented at AMA Workshop in Multivariate Methods in Marketing, January, 1970, 41 pages.

be considered as imbedded in the original 80 dimensional space. Factor analysis reduces this n-dimensional space (n=20) even further to r-space ($r < n$) and projects the n-vectors on this space called the factor space. Hence, it simplifies the description of the original configuration to the minimum dimensions possible.

This simplification in factor analysis is based on the amount of linear dependence, or redundancy, that exists in the data matrix X. If a set of vectors, A, is linearly dependent upon another set of vectors, B, then it is possible to describe the first set of vectors in terms of the second set. Thus, in the above example, if the 20 vectors are linearly dependent, it is possible to describe these 20 vectors in terms of r new vectors ($r < n$) which are, themselves, linearly independent. Only the linearly independent vectors need be retained because the other vectors in the n-space are linear combinations of those in the r-space. The first set of n vectors may explicitly be described by stating their relationship (dependence) to the subset of r.

Hopefully the number of linearly independent vectors will be considerably smaller than the original number, such that their retention will considerably simplify the data. Specifically, the amount of simplification which can be attained is a function of the rank of the matrix. The rank

of a matrix is the maximum number of linearly independent row (or column) vectors of a matrix.[1] In factor analysis, the factor space is of dimension r, and the n-vectors are projected on this r-dimensional space.

To summarize, factor analysis reduces a data matrix X of size nxN to a factor matrix F of size rxN ($r < n$). The greater the difference between r and n, the greater the simplification. The original data matrix X is linearly dependent upon matrix F and the coefficients of this dependence are presented in another matrix A of size nxr. Then, a given observation x_{ji} can be approximated with minimum loss of information by

$$x_{ji} \sim \hat{x}_{ji} = a_{j1}F_{1i} + a_{j2}F_{2i} + \ldots + a_{jr}F_{ri} = \sum_{m=1}^{r} a_{jm}F_{mi} \qquad (1)$$

Then, in matrix notation

$$X \sim \hat{X} = AF$$

Matrix A is called the factor loadings matrix, and matrix F is called the factor scores matrix.

As described in equation (2), a data matrix X can be approximated by X, which is obtained as a product of the factor loadings matrix and the factor scores matrix, However, if a matrix can be expressed as a product of two other

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[1] G. Hadley. Linear Algebra, Reading: Addison Wesley (1961), 138.

matrices, we know that it can also be expressed as the product of an infinite number of pairs of matrices. Thus, there is indeterminacy in factor analysis.

Given the indeterminacy in factor analysis, a set of guidelines was proposed by Thurstone for choosing a single transformation.[1] These guidelines are called the principles of simple structure and are summarized in Harman.[2] Choosing the transformation to impose simple structure is known as the rotation problem in that the principal axes of the factor matrix are rotated from their given position to a new more desirable position. One purpose of the rotation is to achieve a set of axes which allow clear research interpretation, where none was possible prior to the rotation.

A number of analytical rotation procedures are available[3] and are classified as orthogonal and oblique rotations. All of the procedures use some of the principles of simple structure and each will give an invariant factor matrix. The difference between the orthogonal and oblique methods is that orthogonal rotations maintain the orthogonality of the

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[1]Thurstone, L. L. Multiple Factor Analysis, Chicago: U of Chicago Press, 1947, xix and 535.

[2]Harman, H. H. Modern Factor Analysis, Chicago: U of Chicago Press, 1967, 98.

[3]Ibid., 107.

factors during the rotation, while oblique rotations allow correlation among the factors and rotate to pass through the primary clusters of the space.

In general the orthogonal rotation may be represented in these terms using matrix notation

$$B = AT$$

where

$A = (a_{ji})$ initial factor loadings matrix

$B = (b_{ji})$ final factor loadings matrix

$T = (t_{qi})$ orthogonal transformation matrix

A type of orthogonal transformation, the varimax rotation, was used in this study. Harman states that the varimax solution tends to provide the closest solution with respect to both goals of simple structure and factorial invariance.[1] This procedure emphasizes the simplification of the columns or factors of the factor loadings matrix. Individual factor coefficients are altered as a result of the rotation as well as the contributions (characteristic roots) of each of the factors. However, the variance of each variable and the total contribution of all the factors remains the same.

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[1] Ibid., 304-313.

APPLICATION OF FACTOR ANALYSIS

Until recent years, the use of factor analysis in the social and behavioral sciences was dominated by its applications in psychology where it has been a principal tool for several decades.[1] At this point in time, marketing leads the business related disciplines with numerous applications of this and other multivariate tools.[2] Factor analysis has been used in the area of finance. Farrar, for example, used factor analysis for data simplification purposes in a study of investment decision making under uncertainty.[3]

The application of factor analysis in business related research has centered upon three areas: (1) extraction of factors and investigation of their meaning; (2) structural relationship among variables as projected on factor axes; and (3) derivation of factor scores for further investigation.[4]

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[1] Ibid., preface X.

[2] Jagdish Sheth. "Using Factor Analysis to Estimate Parameters," Journal of the American Statistical Association, Vol. 64 (Sept., 1969), 808-822.

[3] Donald E. Farrar, The Investment Decision Under Uncertainty, Englewood Cliffs: Prentice-Hall, Inc., (1962), Chapter 3.

[4] Sheth and Tigert, op. cit., 16-17.

This section will use (2) and its application is discussed below. In investigating the structural relationship among variables, a data matrix is factored in order to observe how the variables behave with respect to the factors and the other variables. The emphasis is upon the configuration of the variables and their alignment with one or more of the factors. The objective is to search for the most promising variables that correlate with one single criterion variable so that they may be used in further analysis. Thus, in this study, the behavior of the ratios with respect to their alignment with common factors was of prime importance so that a select few could represent the total set in further analysis.

PRINCIPAL COMPONENTS ANALYSIS

Principal components analysis was the specific factor analysis solution employed in this study. The general form of the solution was stated in equation (1). This is probably the most widely used technique in factor analysis since the use of the computer has made the calculation problem trivial. Its purpose is to extract maximum variance from the observed variables and the technique is especially useful when a large body of data required simplification.[1]

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[1]Harman, op. cit., 135.

This method involves a rotation of the coordinate axes to a new frame of reference in the total variable space. The n original variables are described in terms of n new principal components which account for a maximum amount of variance of the variables. The sum of the variance of the n principal components is equal to the sum of the variances of the original variables.[1] The differences between principal components analysis and classical factor analysis are discussed in Appendix I which also contains a more formal development of the technique.

ANALYSIS OF MERGER DATA

The original data matrix $X_{(20x80)}$, was the basic source for analysis. A matrix of correlations among the variables, $R_{(20x20)}$, served as the input for factor analysis. The R matrix summarized the information inherent in X while presenting this in a standardized form. Table 3.3 contains the R matrix. Table 3.4 summarizes the output of the original factor analysis, a factor loadings matrix $A_{(20x20)}$. The characteristic roots (or eigen-values) are in column one, and labeled variance. Columns two and three, respectively, indicate the percentage of the total variance explained by the individual factors, and the cumulative

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[1]Harman, op. cit., 136.

TABLE 3.2

MEANS AND STANDARD DEVIATIONS FOR TWENTY RATIOS
IN THREE FIRM GROUPINGS

Non-Acquired Firms			Acquired Firms		
Ratio	Mean	Standard Deviation	Ratio	Mean	Standard Deviation
1	10.47	7.69	1	11.87	7.81
2	34.33	29.89	2	37.03	22.11
3	17.47	16.47	3	14.99	10.93
4	30.08	28.67	4	19.28	23.00
5	26.79	18.46	5	25.76	15.16
6	9.30	10.53	6	8.07	6.22
7	6.22	9.13	7	4.52	4.12
8	10.39	10.30	8	8.82	6.16
9	8.08	15.35	9	9.45	7.27
10	5.39	4.80	10	6.04	4.67
11	34.59	18.60	11	40.65	13.79
12	15.02	15.29	12	14.55	20.59
13	44.14	41.17	13	25.13	37.19
14	4.67	2.09	14	4.79	2.10
15	10.33	21.54	15	4.47	3.01
16	1.36	.65	16	1.41	.52
17	29.85	23.87	17	31.46	12.05
18	18.31	12.98	18	12.22	11.23
19	22.31	14.97	19	13.76	11.21
20	44.58	18.54	20	34.50	15.13
n=40			n=40		

Aggregated Firms		
Ratio	Mean	Standard Deviation
1	11.17	7.73
2	35.68	26.16
3	16.23	13.94
4	24.68	26.39
5	26.28	16.79
6	8.68	8.61
7	5.37	7.09
8	9.61	8.47
9	8.77	11.95
10	5.72	4.72
11	37.62	16.55
12	14.78	18.02
13	34.64	40.14
14	4.73	2.08
15	7.40	15.56
16	1.38	.59
17	30.66	18.80
18	15.26	12.44
19	18.03	13.83
20	39.54	17.56
n=80		

TABLE 3.3

CORRELATION MATRIX FOR TWENTY RATIOS ON EIGHTY FIRMS

	Correlation Matrix									
	1	2	3	4	5	6	7	8	9	10
1	1.000									
2	0.163	1.000								
3	-0.083	-0.025	1.000							
4	-0.232	-0.066	-0.056	1.000						
5	0.262	-0.070	0.186	-0.211	1.000					
6	0.633	-0.017	-0.034	-0.268	0.612	1.000				
7	0.422	-0.077	-0.022	-0.189	0.622	0.950	1.000			
8	0.605	-0.058	0.008	-0.205	0.629	0.992	0.954	1.000		
9	0.678	0.145	-0.008	0.039	0.243	0.454	0.362	0.454	1.000	
10	0.952	0.168	-0.087	-0.239	0.338	0.733	0.577	0.707	0.758	1.000
11	0.271	0.118	-0.157	-0.187	-0.208	-0.005	-0.126	-0.068	0.173	0.190
12	-0.206	-0.276	-0.013	0.587	-0.179	-0.229	-0.173	-0.159	-0.083	-0.252
13	-0.212	-0.209	0.000	0.792	-0.105	-0.245	-0.187	-0.178	0.055	-0.251
14	0.042	0.069	-0.332	0.095	-0.300	-0.341	-0.348	-0.364	-0.009	-0.025
15	-0.053	-0.005	-0.107	0.004	0.023	-0.086	-0.072	-0.076	-0.005	-0.028
16	0.139	0.116	-0.266	-0.001	-0.435	-0.374	-0.413	-0.430	-0.121	0.021
17	0.076	-0.067	0.030	-0.229	0.223	0.501	0.485	0.477	0.104	0.147
18	-0.210	-0.191	-0.068	0.779	-0.137	-0.294	-0.238	-0.229	0.087	-0.243
19	-0.247	-0.177	-0.022	0.757	-0.017	-0.248	-0.170	-0.169	0.099	-0.245
20	-0.231	-0.313	0.038	0.723	-0.244	-0.378	-0.326	-0.306	-0.137	-0.307
	11	12	13	14	15	16	17	18	19	20
11	1.000									
12	-0.137	1.000								
13	-0.197	0.455	1.000							
14	0.002	0.109	0.075	1.000						
15	-0.351	-0.067	0.075	0.080	1.000					
16	0.346	-0.088	-0.026	0.623	0.068	1.000				
17	0.508	-0.196	-0.230	-0.531	-0.319	-0.428	1.000			
18	-0.167	0.478	0.914	0.179	0.155	-0.016	-0.252	1.000		
19	-0.299	0.486	0.869	0.122	0.136	-0.133	-0.323	0.900	1.000	
20	-0.287	0.642	0.783	0.190	0.060	0.164	-0.490	0.745	0.786	1.000

TABLE 3.4

SUMMARY OF FACTOR ANALYSIS: TWENTY RATIOS ON EIGHTY FIRMS

Factor	Variance	Percent Variance	Cumulative Percent
1	6.46	32.32	32.32
2	3.72	18.60	50.92
3	2.49	12.47	63.40
4	1.67	8.38	71.78
5	1.15	5.75	77.54
6	0.99	4.95	82.49
7	0.79	3.97	86.47
8	0.65	3.26	89.74
9	0.52	2.64	92.39
10	0.44	2.24	94.63
11	0.36	1.84	96.47
12	0.23	1.16	97.64
13	0.16	0.83	98.47
14	0.11	0.55	99.03
15	0.07	0.37	99.41
16	0.05	0.26	99.68
17	0.03	0.16	99.85
18	0.02	0.11	99.96
19	0.00	0.02	99.99
20	0.00	0.00	99.99

reduction of variance as the number of factors increase.

The relevant decision with respect to Table 3.4 was how many factors to preserve for further analysis. It was apparent from Table 3.4 that considerable redundancy existed in the original data. The first three factors accounted for over 63% of the variance of the original data matrix, and the first ten factors accounted for over 94% of the total variance.

Cooley and Lohnes noted that Kaiser and others have

suggested that only those factors be retained with corresponding characteristic roots greater than one.[1] With respect to Table 3.4 the roots fall below unity at the sixth factor. The first five factors account for just under 78% of the total variance.

Another criterion is to use enough of the factors to account for at least 90% of the total variance. Sheth employed this method and found, in a study of brand loyalty, that three factors accounted for over 90% of the total variance.[2] In this study, Table 3.4 would indicate the need to retain the first nine factors. This decision was deferred until the varimax rotation was performed into several alternative spaces and the factor loadings matrix A was observed. Table 3.5 is a summary of the rotated factor loadings matrix A which is presented in Table 3.6. This matrix indicated the rotation of the a matrix without further space reduction. It also serves to illustrate the principle of simple structure. Harman noted that weights of zero or one in the first column of each of the coefficients, may be regarded as zero.[3]

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[1]Cooley, W. W. and Lohnes, P. R. Multivariate Procedures for the Behavioral Sciences, New York: John Wiley & Sons, Inc. (1962), 160.

[2]Sheth, "Using Factor Analysis," op. cit., 816.

[3]Harman, op. cit., 310.

TABLE 3.5

SUMMARY OF FACTOR ANALYSIS: ORTHOGONALLY ROTATED FACTOR MATRIX, VARIMAX ROTATION

Factor	Variance	Percent Variance	Cumulative Percent
1	4.35	21.79	21.79
2	3.48	17.40	39.20
3	2.65	13.28	52.49
4	1.45	7.27	59.77
5	1.12	5.61	65.38
6	1.06	5.31	70.69
7	1.04	5.23	75.92
8	1.04	5.21	81.14
9	1.03	5.18	86.32
10	0.97	4.87	91.19
11	0.81	4.06	95.26
12	0.28	1.44	96.71
13	0.24	1.24	97.96
14	0.13	0.66	98.62
15	0.09	0.49	99.12
16	0.08	0.40	99.52
17	0.06	0.30	99.82
18	0.02	0.11	99.94
19	0.01	0.05	99.99
20	0.00	0.00	99.99

This orthogonally rotated factor loadings matrix provided a considerable amount of relevant information, both with respect to the correlations among the variables and their joint contributions to total variance reduction.

First, factor 1 of Table 3.5 was considered. Table 3.5 indicated that factor 1 accounted for 19.9% of the total variance independent of the other factors. As the coefficients of the factors (a_{ji}) in Table 3.6 represents the loadings of each of the variables on the factors, the

TABLE 3.6

ORTHOGONALLY ROTATED FACTOR MATRIX, VARIMAX ROTATION

Ratio	1	2	3	4	5	6	7	8	9	10
1	-0.143	0.305	0.895-	0.079	0.148	0.045	-0.028	0.059	-0.020	-0.026
2	-0.139	-0.072	0.114	0.011	0.026	0.024	-0.010	0.974-	-0.002	-0.098
3	-0.023	-0.033	-0.030	-0.065	-0.089	-0.146	0.976-	-0.009	-0.059	-0.004
4	0.819-	-0.072	-0.069	-0.066	0.026	-0.020	-0.039	0.067	-0.048	0.239
5	-0.057	0.484	0.121	-0.081	-0.149	-0.083	0.117	-0.036	0.030	-0.074
6	-0.169	0.880-	0.378	0.046	-0.108	-0.104	-0.031	-0.018	-0.025	-0.055
7	-0.115	0.946-	0.173	-0.022	-0.091	-0.098	-0.024	-0.042	-0.025	-0.039
8	-0.102	0.889-	0.367	0.007	-0.144	-0.120	0.005	-0.041	-0.021	-0.014
9	0.132	0.183	0.823-	0.097	-0.146	0.031	0.020	0.079	0.017	-0.043
10	-0.164	0.432	0.868-	0.034	0.072	0.023	-0.041	0.071	0.003	-0.062
11	-0.161	-0.147	0.205	0.897-	0.204	-0.009	-0.092	0.042	-0.193	-0.020
12	0.420	-0.080	-0.089	-0.049	-0.053	0.040	-0.007	-0.131	-0.063	0.880-
13	0.962-	-0.068	-0.056	-0.039	-0.018	0.018	-0.016	-0.071	0.008	0.037
14	0.076	-0.247	0.061	-0.110	0.263	0.897-	-0.187	0.028	0.014	0.039
15	0.061	-0.049	-0.002	-0.191	0.028	0.014	-0.060	-0.001	0.974	-0.049
16	-0.046	-0.317	0.081	0.096	0.851-	0.330	-0.135	0.036	0.038	-0.060
17	-0.195	0.453	-0.085	0.692-	-0.312	-0.257	0.010	-0.056	-0.146	-0.085
18	0.950-	-0.127	-0.026	0.002	-0.050	0.089	-0.037	-0.062	0.094	0.067
19	0.929-	-0.081	-0.052	-0.133	-0.119	0.053	-0.019	-0.034	0.054	0.083
20	0.775-	-0.180	-0.085	-0.235	0.213	0.010	0.057	-0.185	-0.027	0.295

Ratio	11	12	13	14	15	16	17	18	19	20
1	0.043	-0.186	-0.040	0.015	-0.027	-0.016	-0.002	0.090	0.008	-0.000
2	-0.024	0.009	0.010	-0.008	-0.000	-0.002	-0.000	0.000	0.000	0.000
3	0.073	0.002	-0.005	0.003	-0.000	0.000	-0.001	0.000	0.000	0.000
4	-0.103	0.025	0.485-	-0.009	-0.006	0.007	-0.001	-0.000	-0.000	-0.000
5	0.830 -	0.011	-0.023	-0.007	0.003	-0.000	-0.000	0.000	0.000	-0.000
6	0.131	-0.038	-0.019	0.007	-0.016	0.012	-0.007	0.029	0.047	-0.026
7	0.133	0.099	0.01	-0.032	0.010	-0.005	0.010	-0.045	-0.073	-0.000
8	0.138	-0.040	-0.018	0.009	-0.001	0.005	-0.009	0.034	0.046	0.026
9	0.051	0.475-	0.024	-0.031	0.008	0.004	0.000	0.002	-0.000	0.000
10	0.040	-0.036	0.002	-0.003	0.024	0.003	0.003	-0.104	-0.012	0.000
11	-0.063	0.003	-0.030	0.002	0.014	-0.093	-0.001	0.001	0.000	-0.000
12	-0.059	-0.005	0.038	0.010	0.001	-0.003	0.001	0.000	-0.000	0.000
13	-0.017	0.005	-0.031	-0.049	-0.179	0.014	-0.142	0.003	0.001	0.000
14	-0.064	0.006	-0.003	-0.000	0.002	-0.005	0.002	0.000	-0.000	0.000
15	0.018	0.003	-0.007	-0.002	0.001	-0.003	0.001	0.000	-0.000	0.000
16	-0.144	-0.032	0.007	0.014	-0.006	-0.003	-0.001	0.000	-0.000	0.000
17	-0.016	0.029	0.039	-0.041	-0.044	0.260	0.006	-0.000	0.000	-0.000
18	-0.018	0.005	-0.039	-0.092	-0.033	0.020	0.195	-0.000	-0.000	0.000
19	0.072	0.064	-0.054	0.042	0.248	-0.048	-0.035	-0.003	-0.000	0.000
20	-0.091	-0.084	-0.027	0.338	0.024	-0.019	-0.012	0.000	0.000	-0.000

relation between any variable and any factor can be directly observed. Each row (a_j) in the matrix is a vector of unit length. Thus $\sum_{j=1}^{N} (a_{ji})^2 = 1$, and the a_{ji}'s have an analagous interpretation to the correlation coefficient.[1] The first factor has high loadings on variables 4, 13, 18, 19, and 20. For example, variable 13 has a coefficient of 0.96 indicating that $(0.96)^2$ or 92% of this variable's total variance is explained in factor 1. Table 3.1 identifies each of the above variables as measuring leverage. In that no other ratios have high loadings on factor 1, a leverage label can be attached to this factor. From Table 3.5 it was noted that the leverage factor dominated the others. Thus, the quality of financial leverage was retained as a measure of group differences in later analysis.

The same analysis and interpretation was used for factor 2 and the high loading coefficients were noted. Table 3.1 identified these variables as measuring profitability. That label was attached to factor 2. The same procedure was followed for the remaining factors.

However, it was rapidly apparent that although variables could be identified in each of the subsequent factors, the factors themselves contributed little to the explanation

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[1]Sheth and Tigert, op. cit., 7.

of the total variance. Also, it was noted that variables originating in the first factors were being independently identified with later insignificant factors. Variable 8 in both factors 2 and 10 is an example of this occurrence. It was apparent that further reduction in the sample space could be accomplished with little loss of information.

Table 3.7 summarizes the rotation of the original A matrix into ten dimensions. Table 3.5 noted that the first ten dimensions accounted for over 91% of the total variance. The same procedure was followed as with the first rotation in that the highest loading variables for each factor were identified and the factors were labelled to represent the class of ratios which were identified with that factor. Note that the first several factors are the same as in Table 3.6, and that although the first four factors explained two-thirds of the total variance, all of the factors had roots greater than one.

A third rotation into 6 dimensions was summarized in Table 3.8 with subsequent analysis of the loadings and labelling of the factors. Once again the leverage and profitability factors were the most significant. Factors 3 was an activity factor and the significant ratios within that factor related to alternative measures of turnover with respect to sales and total assets. Factor number 4 was

TABLE 3.7

VARIMAX ROTATION INTO TEN SPACE: SUMMARY OF FACTORS AND ROTATED FACTOR MATRIX

Summary

Factor	Variance	Percent Variance	Cumulative Percent
1	4.48	23.67	23.67
2	3.76	19.87	43.55
3	2.48	13.13	56.69
4	1.86	9.86	66.55
5	1.50	7.95	74.51
6	1.13	5.97	80.48
7	1.05	5.55	86.04
8	1.03	5.46	91.51
9	0.93	4.94	96.45
10	0.66	3.53	99.99

	1	2	3	4	5	6	7	8	9	10
1	-0.166	0.423	0.797-	0.263	0.100	0.035	0.058	0.001	-0.009	-0.089
2	-0.143	-0.074	0.122	0.046	0.007	-0.011	0.967-	-0.003	-0.095	-0.010
3	-0.028	-0.057	-0.006	-0.175	-0.081	0.937-	-0.011	-0.079	-0.004	0.084
4	0.858-	-0.069	-0.063	-0.018	-0.045	-0.052	0.124	-0.054	0.254	-0.149
5	-0.061	0.633	0.064	-0.134	-0.068	0.220	-0.023	0.071	-0.075	0.659
6	-0.183	0.898-	0.336	-0.159	0.052	-0.036	-0.021	-0.030	-0.050	0.032
7	-0.119	0.916-	0.170	-0.207	-0.018	-0.063	-0.041	-0.040	-0.045	0.072
8	-0.115	0.906-	0.329	-0.197	0.010	-0.000	-0.044	-0.027	-0.009	0.041
9	0.122	0.151	0.917-	-0.145	0.070	-0.034	0.073	-0.002	-0.047	0.136
10	-0.183	0.507-	0.809-	0.134	0.043	-0.015	0.073	0.011	-0.047	-0.056
11	-0.172	-0.147	0.203	0.177	0.901-	-0.068	0.037	-0.181	-0.016	-0.045
12	0.449	-0.094	-0.079	-0.028	-0.049	-0.017	-0.135	-0.064	0.863-	-0.029
13	0.960-	-0.063	-0.041	0.004	-0.019	0.027	-0.080	0.016	-0.012	-0.018
14	0.068	-0.325	0.113	0.691-	-0.211	-0.382	0.014	-0.074	0.080	0.249
15	0.057	-0.050	0.004	0.031	-0.202	-0.074	-0.003	0.965-	-0.049	0.024
16	-0.039	-0.271	0.017	0.891-	0.156	-0.095	0.043	0.061	-0.076	-0.202
17	-0.203	0.388	-0.059	-0.481	0.688-	-0.043	-0.056	-0.164	-0.079	0.009
18	0.942-	-0.151	0.015	-0.001	-0.003	-0.074	-0.075	0.090	0.033	0.075
19	0.926-	-0.097	0.000	-0.067	-0.163	-0.033	-0.052	0.047	0.059	0.150
20	0.792-	-0.134	-0.119	0.238	-0.213	0.129	-0.202	-0.008	0.274	-0.179

described by two measures of liquidity. Factors 5 and 6 respectively were uniquely identified by dividend payout and price/earnings ratios.

A comparison of Tables 3.7 and 3.8 shows that several ratios identified with the last five factors of Table 3.7 did not enter any of the new factors in Table 3.8 as represented by their respective coefficients. This confirmed what was apparent--the first five factors did not describe all of the variance in original space and there were ratios which contributed uniquely to the reduction of variance. However, they tended to account for only small portions of the variance.

The factor analysis had served its purpose well in that from an original space of 20 dimensions, less than ten could be used to represent the great portion of the variance of the total space. The exact number of dimensions used remained flexible so as to allow the discriminant analysis some alternative input matrices. In this application, the usefulness of the ratios for group separation was important, and the number of dimensions in the sample-space was made dependent upon the results of the subsequent discriminant model.

The method of arriving at ratios, given alternative factors and factor loadings was simple and straightforward.

TABLE 3.8

VARIMAX ROTATION INTO SIX SPACE: SUMMARY OF FACTORS AND ROTATED FACTOR MATRIX

Summary			
Factor	Variance	Percent Variance	Cumulative Percent
1	4.76	28.89	28.89
2	4.32	26.19	55.08
3	3.15	19.09	74.18
4	1.78	10.84	85.02
5	1.29	7.86	92.89
6	1.17	7.10	99.99

Ratio	1	2	3	4	5	6
1	-0.157	0.908	-0.185	0.134	0.104	-0.018
2	-0.157	0.074	-0.083	-0.001	0.811-	-0.039
3	-0.028	-0.056	0.232	-0.008	0.028	-0.896-
4	0.888	-0.095	-0.032	0.021	0.007	0.027
5	-0.127	0.458-	0.509	-0.304	-0.131	-0.124
6	-0.227	0.787-	0.492	-0.023	-0.161	0.141
7	-0.174	0.667-	0.570	-0.103	-0.235	0.167
8	-0.151	0.781-	0.525	-0.056	-0.196	0.097
9	0.176	0.784-	0.009	0.108	0.320	-0.059
10	-0.176	0.951-	-0.052	0.067	0.121	0.018
11	-0.169	0.079	-0.135	0.842-	0.206	0.218
12	0.609-	-0.116	-0.098	0.098	-0.433	-0.100
13	0.933-	-0.072	0.008	-0.053	-0.017	0.018
14	0.080	0.017	-0.794-	-0.122	-0.056	0.214
15	0.044	-0.045	-0.078	-0.717-	0.214	0.263
16	-0.088	-0.032	-0.850-	0.137	0.039	0.177
17	-0.022	0.108	0.693-	0.564-	-0.002	0.231
18	0.937	-0.079	-0.047	-0.079	0.030	0.096
19	0.927-	-0.058	0.021	-0.195	-0.006	0.002
20	0.815-	-0.145	-0.272	-0.111	-0.300	-0.145

It has been widely used and involved choosing the variable with the highest loading from each of the significant factors.[1] In that for several of the factors more than one ratio existed with similar high loadings, some flexibility was afforded.

The ratios carried forward from the factor analysis are listed below by class. The first ratio listed had the highest coefficient on that factor, while others listed for the same factor were ratios with slightly lower coefficients.

(1) leverage--ratios 13 and 18, 19

(2) profitability--ratios 1 and 10

(3) activity--ratios 14 and 15 and 16

(4) liquidity--ratios 11 and 17

Additionally, from Table 3.7 it was noted that ratios 2, 3, and 12 each had contributed somewhat to the variance reduction. This information provided the basis with which a discriminant model was developed to test for group differences with respect to the above qualities.

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[28]Sheth and Tigert, op. cit., 24.

CHAPTER IV

MULTIPLE DISCRIMINANT ANALYSIS

INTRODUCTION

The result of the factor analysis performed upon the original data was to summarize and simplify the data for further use. The reduced data set was the basic input into a discriminant analysis which tested group differences and attempted to predict group membership from the discriminant function which best separated the groups.

This chapter is divided into four parts: Part I develops the statistical tool of multiple discriminant analysis (MDA), and relates other applications of the tool. Part II develops a model based upon the original observed samples. The quality of the model is then evaluated. Part III evaluates basic assumptions of the discriminant model and concludes that the assumptions can better be satisfied with a re-formulation of the samples into more naturally defined, mutually exclusive groups. This was accomplished with factor analysis. Part IV constructs and tests both a comparative model to that in Part II and an

improved model based on natural groups, as defined. This model was evaluated and then validated as to its ability to accurately identify firms not included in the development of the model itself.

At each step, the financial variables used in the models are analyzed. They are evaluated with respect to group differences in a univariate context and then their individual contributions to the total discriminant function in a multivariate framework is studied. Finally, the results are summarized with respect to how the financial qualities differ between the two groups.

MULTIPLE DISCRIMINANT ANALYSIS

Multiple discriminant analysis (MDA) is a multivariate technique for the classification of a set of objects, by a set of independent variables, into two or more exclusive and exhaustive categories. With respect to the Kendall classification discussed in the preceding chapter, MDA would be considered as part of analysis of dependence. MDA is an alternative to multiple regression when the dependent variable is nonmetric (qualitative).[1]

The primary objective of MDA is to correctly classify entities into mutually exclusive groups by the statistical

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[1]Sheth, op. cit., 14.

decision rule of maximizing the ratio of among-group to within-groups variance-covariances on the profile developed by the independent variables. In addition, the discriminant analysis reveals which of the specific variables employed accounted for the largest portion of the intergroup differences.

One of the first known applications of MDA was by M. Barnard in 1935 to date a series of Egyptian skulls.[1] R. A. Fisher then applied the method in 1936,[2] and the development of the tool was extensive from that time and widely used in the areas of biometrics and psychometrics.[3] In the business related areas, MDA has been used in marketing for a number of purposes,[4] and has had application in finance. One early use of MDA in finance was Walter's study

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[1]M. M. Bernard. "The Secular Variations of Skull Characters in Four Series of Egyptian Skulls," Annals of Eugenics, VI (1935), 352-371.

[2]R. A. Fisher. "The Use of Multiple Measurements in Taxanomic Problems," Annals of Eugenics, VII (1936), 179-188.

[3]D. V. Tiedeman. "The Utility of the Discriminant Function in Psychological and Guidance Investigations," Harvard Educational Review, XXI, No. 2 (Spring, 1951), 71-80.

[4]Sheth, op. cit., 14-17.

of price/earnings ratios of large corporations[1] and several applications of the tool are apparent in the literature.[2] The recent study by Altman,[3] was an attempt to develop financial profiles of firms for the purpose of using a discriminant model to predict likelihood of bankruptcy. The predictive accuracy of Altman's model, 90% accuracy up to three years prior to bankruptcy, suggested the potential of both MDA and the multivariate framework in financial analysis.

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[1]J. E. Walter. "A Discriminant Function for Earnings Price Ratios of Large Industrial Corporations," Review of Economics and Statistics, Vol. XLI (February, 1959), 44-52.

[2]H. Myers and E. W. Forgy. "Development of Numerical Credit Evaluation Systems," Journal of American Statistical Association, Vol. 50 (September, 1963), 797-806.

R. J. Monroe and M. A. Simkowitz. "Investment Characteristics of Conglomerate Targets: A Discriminant Analysis," Unpublished paper given at Southern Finance Association meetings, Fall, 1970.

[3]Altman, op. cit., 589-609.

THE MULTIPLE DISCRIMINANT MODEL FOR TWO GROUPS[1]

Given two mutually exclusive groups with profiles measured by a set of n independent variables, the discriminant function is of the form

$$Z_i = b_1X_{1i} + b_2X_{2i} +\ldots,+ b_nX_{ni} \quad (1)$$

where $b_1, b_2,\ldots, b_n$ are discriminant coefficients

and $X_{1i}, X_{2i},\ldots, X_{ni}$ are independent variables.

In the two group case there exists only one discriminant function. The maximum number of Z_i in the general case is the smaller of G-1 or n, where G is the number of groups. In the two-group case the index, i, is unnecessary as only one discriminant function exists.

Equation (1) is a linear combination of the variables, $X_1, X_2,\ldots, X_n$, which maximally differentiates among the groups. The task of the discriminant analysis is that

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[1]A more rigorous derivation of the tool for the general case of n groups can be found in either of the references listed below. This development is standard as put forth in this chapter and benefited from Tatsouaka and Morrison.

M. M. Tatsouaka. Discriminant Analysis: The Study of Group Differences, No. 6, Champaign, Illinois: Institute for Personality and Ability Testing (1970).

J. G. Bryan. "The Generalized Discriminant Function, Mathematical Foundation and Computational Routine," Harvard Educational Review, XXI, No. 2 (Spring, 1951), 90-95.

D. G. Morrison. "On the Interpretation of Discriminant Analysis," Journal of Marketing Research, Vol. 6 (May, 1969), 156-163.

of deriving the set of b_i's.

Thus, given n variates x_1, x_2,..., x_n representing measurements on G groups (two groups of firms in this context), there are N_g (g=1,2,...,G) firms with group g. If there are N firms in group g, the measure of the j^{th} variable of the p^{th} firm in the g^{th} group would be x_{pgi}.

Each variate, x_i, has a group mean for group j of the form

$$\bar{x}_{gj} = \frac{1}{N} \sum_{p} x_{pgj} \tag{2}$$

Equation (1) with respect to an individual firm is written

$$y = v_1x_1 + v_2x_2 +...,+ v_nx_n \tag{3}$$

and the group mean of y is

$$\bar{y}_g = \frac{1}{N} \sum_{p} y_{pg} \tag{4}$$

and the sum of squares among groups for y is

$$\sum_{g} N_g \bar{y}_g^2 \tag{5}$$

and the sum of squares within groups is

$$\sum_{p,g} (y_{pg}-\bar{y}_g)^2 \tag{6}$$

The problem is to determine the coefficients, $v_1, v_2, ..., v_n$ so that the ratio λ of the among groups sum of squares to the within groups sum of squares is maximized.

Expressed in terms of matrix notation, the among groups sum of squares can be written as a symmetrical matrix

$$A = [a_{ij}] = \sum_{g} N_g \bar{x}_{gi} \bar{x}_{gj} \quad \text{and } a_{ij}=a_{ji} \ (i,j\ 1,2,\ldots,n) \tag{7}$$

and the within groups sum of squares as a symmetrical matrix

$$W = [w_{ij}] = \sum_{p,g} (x_{pgi}-\bar{x}_{gi})(x_{pgj}-\bar{x}_{gj}) \text{ and } w_{ij}=w_{ji} \tag{8}$$

and the column vector

$$\underset{\rightarrow}{V} = [v_j] \tag{9}$$

Then, equations (5) and (6) respectively become $\underset{\rightarrow}{V}'A\underset{\rightarrow}{V}$ and V'WV. Their ratio is the criterion maximized with respect to the v_i

$$\lambda = \frac{\underset{\rightarrow}{V}'A\underset{\rightarrow}{V}}{\underset{\rightarrow}{V}'W\underset{\rightarrow}{V}} \tag{10}$$

Upon setting the partial derivatives of λ, with respect to the v_i's equal to zero, we arrive at

$$(\underset{\rightarrow}{V}'W\underset{\rightarrow}{V})A\underset{\rightarrow}{V} - (\underset{\rightarrow}{V}'A\underset{\rightarrow}{V})W\underset{\rightarrow}{V} = 0 \tag{11}$$

Dividing through by $\underset{\rightarrow}{V}'N\underset{\rightarrow}{V}$ and collecting terms we get

$$(A - \lambda W)\underset{\rightarrow}{V} = 0 \tag{12}$$

which simplifies to

$$(R - \lambda I)\underset{\rightarrow}{V} = 0 \tag{13}$$

where I is the identity matrix and $R = W^{-1}A$

An equation of the form of (13) where R is a matrix of size nxn, with known elements, $\underset{\rightarrow}{V}$ is an unknown n-dimensional column vector, and λ, is an unknown scalar, is a well problem in applied mathematics.[1] The derivation of the

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[1]Tatsuoaka, op. cit., 31.

solution will not be shown here. The derivation is shown in Tatsuoaka for the present context, and Morrison for the general case.[1]

The solution of (13) for the v_i is determined by the latent vectors of R and their corresponding latent roots. In the two group case, only one latent vector provides a set of combining weights $v_1 v_2,\ldots,v_n$ such that the resulting linear combination as expressed in (1) and (3) has the largest possible discriminant criterion value among all linear combinations of the n predictor (independent) variables.[2]

CLASSIFICATION PROCEDURE

For the purpose of classification of firms using the discriminant model, the following procedure was employed.[3] Let each individual's discriminant score, Z_i, be a linear function of the n independent variables. Thus, as in equation (1), and for this context, i=1,2,...,80, and

$$Z_i = b_0 + b_1 X_{1i} + v_2 X_{2i} +\ldots,+ b_n X_{ni} \qquad (14)$$

The classification procedure is as follows

if $Z_i > Z_{critical}$, classify firm i as belonging in group 1

if $Z_i < Z_{critical}$, classify firm i as belonging in group 2

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[1]Tatsuoaka, op. cit., 31-33.

[2]Tatsuoaka, op. cit., 33.

[3]Morrison, op. cit., 157-158.

The classification boundary will be the point (or the locus of points in the case of more than one discriminant function) where

$$b_0 + b_1\bar{\bar{X}}_1 + b_2\bar{\bar{X}}_2 +\ldots,+ b_n\bar{\bar{X}}_n = \bar{\bar{Z}}_{critical}$$

where the $\bar{\bar{X}}_i$ are the respective grand means for each of the independent variables.

This procedure is especially advantageous in the case of two groups and one discriminant function because the classification is performed in one dimension. For the above case, the higher the Z-score, the more firm i is like group 1. Additionally, the influence of the independent variables can be observed with respect to the Z-score.[1] That is to say, if b_2 is a coefficient near 1.0, then the actual value of X_2 will have an important effect upon the Z-score for a given firm, whereas if b_2 were near zero, changes in the actual value of X_2 for any given firm would have little effect upon the Z-score.

MDA MODEL

The reduced set of variables determined by the factor analysis was used to develop the discriminant model. It should be noted that while the factor analysis did analyze the redundancy of the original data matrix, the reduction of the matrix to a subset of variables which summarized the

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[1]Morrison, op. cit., 157.

total without significant loss of information did not suggest or imply which would possess discriminating power in the model. Therefore, while the factor analysis did assist in reducing the number of alternatives, it did not obviate the need to analyze alternative combinations of variables to form the discriminant function.

All of the following criteria entered into the selection of the final variables: (1) ability of the function to separate groups; (2) ability of the function to classify firms; (3) relative contribution of alternative variables in the discriminant function; (4) inter-correlations among the independent variables. With respect to (4) it should be noted that if only one ratio were employed from each of the factors from the factor analysis, they tended to minimize collinearity of the discriminant function among the independent variables.

The final discriminant function was the result of numerous computer runs and represented an optimization of the above criteria. No claim is made that this function represents the best combination, but it should be noted that testing similar models with other combinations, both adding and changing variables, did not significantly improve the group separation or the classification ability of the model. Additionally, this particular function was

similar in both respect to combinations of variables from the significant factors suggested by the factor analysis. The classification of the alternative models was especially stable, with overall classification accuracy within two or three percentage points of the model chosen.

The following discriminant function was developed

$$Z = .005X_1 + .934X_2 + .064X_3 + .352X_4$$

where

X_1--NET INCOME/TOTAL ASSETS. This ratio measures the earnings of the firm after taxes and interest charges, and represents the potential funds available for distribution to the owners. This ratio was employed to represent a measure of the firm's profitability. This ratio had the highest factor loading coefficient on the profitability factor.

X_2--SALES/TOTAL ASSETS. This ratio is an indication of how efficiently the assets of the firm are being employed with respect to the generation of sales. The higher the ratio value, the greater the efficiency of the assets in producing sales. If acquired firms were systematically inefficient, with excess liquidity and under utilized assets, ratio X_2 would be lower for the acquired group than for the non-acquired group.

X_3--NET WORKING CAPITAL/SALES. This ratio measures the liquid assets of the firm relative to its sales. Liquid

assets, as measured by net working capital, are current assets minus current liabilities. This ratio implicitly examines the firm's management of current assets and current liabilities. A firm with a liberal credit policy will have larger accounts receivable balances relative to sales. A firm with a poor inventory management will have large inventory balances relative to sales. The same would apply to the level of cash and near-cash. The inefficient management of these assets would render the firm more liquid than an efficiently managed firm. The opportunity would exist for another firm to take over the first firm and reduce the levels to an efficient level and employ the excess liquidity elsewhere. Thus, excess liquidity would increase a firm's attractiveness as a merger target and the acquired firms would be expected to be more liquid than the non-acquired sample.

X_4--LONG TERM LIABILITIES/TOTAL ASSETS. This ratio is a measure of the degree of financial leverage which exists in the capital structure. The higher the level of debt for a firm, the higher the ratio. With respect to the Lewellen hypothesis, acquired firms should have systematically lower levels of borrowing. Thus, upon acquisition, the acquiring firm who is generally an aggressive user of financial leverage, will have increased borrowing power for the combined

enterprise.

GROUP DIFFERENCES

An analysis was made as to how the groups differed with respect to each of the above ratios, and how well any of the ratios could have separated the groups on a univariate basis. Table 4.1 presents the group means for each of the ratios in the discriminant function and also presents the F-statistic from a one-way analysis of variance test of the difference of the group means on a univariate basis. First, from a univariate point of view, only the leverage variable indicated a difference between the two samples which was statistically significant. If a univariate methodology had been employed, the only conclusion which could have been statistically valud was that acquired firms had lower levels of leverage. The other observed differences, namely that acquired firms were more profitable, had higher turnover of assets, and were more liquid, could have occurred due to chance.

Table 4.2 presents the statistics of the multivariate discriminant function. The centroid is the multivariate equivalent of the mean and the Wilks lambda is the measure of the distance between the centroids. The significance of the distance is approximated by the F-statistic. For the two groups, the F-statistic was 2.12 which was

TABLE 4.1

UNIVARIATE TESTS OF SIGNIFICANCE FOR
GROUP MEANS: OBSERVED GROUPS

Variable	Ratio	Group Means NON-ACQ	Group Means ACQ	F
X_1	net income/assets	5.40	6.05	.38
X_2	sales/assets	1.36	1.41	.15
X_3	NWC/sales	29.86	31.47	.15
X_4	LT liabilities/assets	22.31	13.77	8.35
		n=40	n=40	
		F(1,60)(.01) = 7.08		
		F(1,60)(.10) = 2.79		

TABLE 4.2

MDA: GROUP DIFFERENCES, OBSERVED GROUPS

Group	Centroids	
1	Non-ACQ	11.05
2	ACQ	8.20
	Wilks lambda	0.899
	F(4,72) =	2.12
	F(4,60)(.10) =	2.04
	F(4,60)(.05) =	2.53

significant at the 0.10 level. Thus the hypothesis that the differences were attributable to chance was rejected, and further analysis was possible.

Analysis of the independent variables was of interest to indicate their individual influence upon the discriminant function. This was not directly apparent from the coefficients in the discriminant function because the ratios were measured on a different scale. The scale factors were removed and Table 4.3 indicates the relative importance of the four ratios. The most significant of the four ratios was the ratio measuring leverage. This finding was consistent with conclusions of the univariate tests. Liquidity was the second most important variable in group discrimination. Although not significant in a univariate context, it was second only to leverage as a contributor to group

TABLE 4.3

MDA: SCALED VECTORS AND DISCRIMINANT FUNCTION, OBSERVED GROUPS

Variable	Ratio	Discriminant Coefficient	Scaled Vector	Rank
X_1	net income/assets	.005	.217	4
X_2	sales/assets	.934	4.915	3
X_3	NWC/sales	.064	10.639	2
X_4	LT liabilities/assets	.352	41.102	1

discrimination. The activity variable and the profitability variable were third and fourth respectively. It should be noted from the size of the scaled vector that the group differences with respect to profitability added very little to the total model. However, the joint effect of the four variables with respect to the two groups indicated that the groups could be differentiated.

To further test the ability of the discriminant function to discriminate between the groups, the individual firms were then subjected to a classification into one of the two groups based upon their individual discriminant score. The score was calculated by substituting the actual variable value for each firm into the X_i of the model. The resulting Z-scores were used to compare with the $Z_{critical}$ and classify into one of the groups. Table 4.4 is a classification matrix with respect to all 80 firms. The interpretation of Table 4.4 is as follows. For the 40 firms in group 1 (non-acquired firms), 19 were classified as non-acquired by the Z-score classification, and 21 were classified as acquired firms. For the second group (acquired firms) the classification was quite accurate, assigning 33 of the 40 firms to the correct group. The overall classification accuracy was 65%. A null hypothesis was tested with respect to the level of classification accuracy. Acceptance

TABLE 4.4

MDA: CLASSIFICATION MATRIX, OBSERVED GROUPS

	Predicted				
Actual	NON-ACQ		ACQ		
	(%)	#	(%)	#	
NON-ACQ	(48)	19	(52)	21	40
ACQ	(17)	7	(83)	33	40
		26		56	80

$t = 2.7$

$t(60)(.005) = 2.7$

$$t = \left(\frac{p-.5}{\frac{.5(1-.5)}{n}}\right)$$

p = proportion correct

n = 80

of the null hypothesis would imply that the model had no ability to classify firms accurately, or that the same level of accuracy could have occurred by chance. The t-statistic of 2.7 allowed rejection of the null hypothesis at the .005 level of significance indicating that the model did possess discriminating power.

However, the poor classification of the sample of non-acquired firms raised some doubt with respect to the usefulness of the model in an operational sense. With the original sample of 80 firms, 55 or almost 70% were classified as acquired. This result was further examined and explanation

was sought for how and why this could have occurred. The next section reports the examination of the assumptions of the discriminant model and the explanation of the initial results when all assumptions were considered.

THE NATURAL-GROUPS ASSUMPTION OF MDA

The nature of the a priori groups which were input into the discriminant model was an important basic assumption of the model. The assumption was that the groups were naturally defined. The groups must be such that no individual in the sample belonged to more than one of them. Tatsuoaka states that discriminant analysis cannot be used when overlapping groups are sought to be compared. In situations such as this, the groups must be "purified" by discarding individuals who are members simultaneously of more than one group.[1]

The natural group assumption was examined with respect to the testing of the observed groups from the original sample. An argument in defense of the observed groups was that they did satisfy the above assumption of no simultaneous membership. A firm was either acquired or non-acquired at a point in time. Thus, no firm in the observed sample could be simultaneous members of both groups.

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[1]Tatsouaka, op. cit., 38-39.

However, a re-examination of the purpose served by the sample and test, and a consideration of the actual results of the discriminant analysis raised doubt as to the validity of the above argument.

The samples were taken to represent (1) firms already acquired in industrial mergers, and (2) eligible firms not yet acquired. However, the hypothesis tested was with respect to group differences on financial variables and financial profiles. The financial profiles procedure, as well as the firms sampled, developed the input criteria for the discriminant analysis. Further interpretation of the behavior of financial profiles was relevant. By way of example, a firm in the non-acquired sample may have measurements on the variables such that its profile would be very similar to most of the acquired firms. Conversely, an acquired firm could have a profile more similar to that of the non-acquired firms.

The results of the discriminant analysis indicated group differences were significant. However, the subsequent classification, although possessing statistically significant predictive power, indicated that although acquired firms were quite similar as a group, much inconsistency was present in the non-acquired sample. Thus there were a number of firms, who had not been acquired, with financial

profiles similar to those of acquired firms. These firms were attractive with respect to the financial variables employed. It should be remembered that these variables constituted a "best" representation of the original 20x80 sample space in a reduced dimension, as determined by the factor analysis. The generalization of this analysis was that the variables employed represented the information contained in the financial statements. Therefore, the alignment of firms was based on these profiles and the results to profiles was not accurate also with respect to alignment with observed samples.

However, the significance of the group differences from the observed samples established that if a firm was acquired, its financial qualities were different from the general population of non-acquired firms. This did not rule out the existence of a subset of the non-acquired population which had the same attractiveness in a financial sense as acquired firms. Furthermore, the acquired population itself would be expected to contain firms who had financial profiles much different from those of other acquired firms and quite similar to firms in the non-acquired, non-attractive population.

The argument that the samples represented "natural" or mutually exclusive groupings was true with respect to the

merger transaction criterion itself. But with respect to financial profiles there existed much overlapping of groups and the purification of groups was needed.

A new natural grouping was proposed with membership based upon attractiveness for acquisition. The groups were labelled "attractive" and "non-attractive" with respect to acquisition. In order to accomplish the natural groupings, factor analysis was again employed.

FACTOR ANALYSIS OF FIRMS

The original data matrix, X, (20x80) was transposed and the new matrix, X^T (80x20), was the basis for the factor analysis. The difference between this operation and the original factor analysis is summarized below.

The factor analysis employed in Chapter III was for the purpose of summarizing and simplifying the data with respect to the ratios. To the extent that linear dependency existed among the 20 ratios used, these could be reduced to a much smaller set without much loss of information. In that analysis it was discovered that four factors explained the majority of the variance of the entire set. A rotation of the principal axes of the space and transformation of the factor loadings matrix to impose simple structure, allowed the factors to be identified and labelled with respect to financial qualities under examination. Thus the emphasis

of that factor analysis was to identify how ratios could be reduced to a smaller number without loss of information.

The emphasis of the second application of factor analysis was not to resolve the 80 firms into a smaller set of firms without loss of information, but to align the firms with a small number of factors.[1] The same relationship with respect to linear dependency applied to the firms. To the extent that firms were similar (on the variables used) they would cluster together onto one factor. This was analogous to one aspect of the first application. The leverage ratios were all similar quantities and, as expected, aligned themselves together with high loadings on one factor. No other ratios loaded highly on that factor and the factor was labelled a leverage factor. Similarly, to the extent that the firms had closely related qualities, they would align on one factor.

The result of the factor analysis upon the firms is presented in Table 4.5. If all of the 80 firms had been completely independent of one another in a financial sense, a large number of non-zero factors would have resulted (≤ 80). Table 4.5 summarizes only the first 20 factors in that all of the subsequent factors were zero. In order to have two

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[1] J. N. Sheth and D. Tigert, op. cit., 16-20.

TABLE 4.5

FACTOR ANALYSIS: SUMMARY OF FACTOR MATRIX, FIRST TWENTY-ONE ROOTS

Factor	Variance	Percent Variance	Cumulative Percent
1	817145.15	68.46	68.46
2	173611.86	14.54	83.01
3	54381.31	4.55	87.57
4	35875.82	3.00	90.57
5	26542.59	2.22	92.80
6	20741.74	1.73	94.53
7	18335.62	1.53	96.07
8	14404.84	1.20	97.28
9	10435.81	0.87	98.15
10	8054.03	0.67	98.83
11	6548.67	0.54	99.37
12	3818.17	0.31	99.69
13	1572.78	0.13	99.83
14	1019.06	0.08	99.91
15	643.66	0.05	99.97
16	244.84	0.02	99.99
17	79.31	0.00	99.99
18	24.32	0.00	99.99
19	9.44	0.00	100.00
20	2.92	0.00	100.00
21	0.00	0.00	100.00

natural groupings of firms for further analysis, it was hoped that the majority of the firms would load on two factors. Table 4.5 indicates that this was the case. The first two factors accounted for 83% of the total variance. This was sufficient and only the first two factors were retained for further analysis. A varimax rotation was imposed upon the factor scores matrix and the new factor loadings are presented in Table 4.6. Firms were then individually

identified to each of the factors by examining each factor loading coefficient for every firm and grouping the firm to the factor which contained the higher loading.

With respect to Table 4.6, the observed sample of non-acquired firms can be identified by variables 1-40, and the acquired firms by numbers 41-80. If all acquired firms were similar to each other with respect to the financial criteria tested, and at the same time different from all non-acquired firms, then the natural groupings, as indicated by the factors in Table 4.6, and the observed groupings (from the original sample), would coincide. It can be seen from the two factors that there was frequent crossover from the observed groups to the two factors which represented the natural groups.

Thus, Table 4.6 indicated that the original 80 dirms could be assembled into two groups other than acquired and non-acquired. Furthermore, the crossover of firms indicated that the same qualities found in acquired firms also existed in some of the non-acquired firms. In that the majority of the acquired firms aligned with factor 1, and the majority of the non-acquired firms aligned with factor 2, the respective factor labels assigned were attractive and non-attractive.

A test was performed with respect to the observed

TABLE 4.6

ORTHOGONALLY ROTATED FACTOR MATRIX, VARIMAX ROTATION:
EIGHTY FIRMS INTO 2-SPACE

Factor	Variance	Summary Percent Variance	Cumulative Percent
1	31.95	55.58	55.58
2	25.53	44.41	99.99

	1	2		1	2
1	0.860	-0.221	41	0.872	0.304
2	0.786	0.479	42	0.900	0.103
3	0.670	-0.677	43	0.843	-0.142
4	0.355	0.903	44	0.959	-0.095
5	0.721	0.564	45	0.836	0.272
6	0.128	0.859	46	0.895	-0.171
7	0.442	-0.501	47	0.485	0.810
8	0.765	0.461	48	0.331	0.749
9	0.337	-0.676	49	0.910	0.377
10	-0.038	0.831	50	0.389	-0.543
11	0.211	0.927	51	0.875	0.442
12	0.760	-0.116	52	0.870	-0.084
13	0.307	0.807	53	0.048	-0.687
14	0.897	-0.077	54	0.894	-0.208
15	-0.121	0.948	55	0.242	0.112
16	0.565	-0.670	56	0.007	0.832
17	-0.044	-0.531	57	0.299	0.751
18	0.119	0.812	58	0.685	0.127
19	0.857	-0.660	59	0.878	0.111
20	0.630	-0.660	60	-0.011	0.798
21	0.835	0.471	61	0.561	0.738
22	0,915	0.310	62	0.871	0.296
23	0.899	0.002	63	0.945	-0.056
24	0.003	0.934	64	0.960	0.117
25	0.743	0.429	65	0.397	0.480
26	0.634	-0.663	66	0.780	0.257
27	0.060	0.855	67	0.706	0.460
28	0.923	0.085	68	0.627	0.497
29	0.242	0.182	69	0.742	0.425
30	0.126	-0.443	70	0.565	0.285
31	-0.251	0.800	71	0.900	0.239
32	-0.152	0.904	72	0.537	-0.655
33	-0.293	-0.458	73	-0.023	0.875
34	0.294	0.864	74	0.815	0.044
35	-0.175	0.955	75	0.326	0.837
36	0.333	-0.286	76	0.010	0.927
37	0.037	-0.619	77	0.485	-0.680
38	0.758	0.542	78	0.966	0.082
39	-0.101	-0.577	79	0.974	-0.003
40	-0.550	-0.137	80	0.763	0.556

groupings represented by the original sample and the new natural groupings in Table 4.6. The results of both the groupings of the firms and the test of the groupings is presented in Table 4.7. The proposed test was to establish if the new groupings could have been attributed to chance, rather than to similarities among firms within the observed groups. The hypothesis of no difference would predict that alignment of the observed groups would be random with respect to the natural groups. A rejection of the null hypothesis would accept the belief that the attractiveness criterion accounted for the new groupings. An important result of the rejection of the null hypothesis was that the formation of two groups of attractive and non-attractive could be retained for further use. The Table 4.7 test results allowed rejection of the null hypothesis at the .05 level of significance.[1] Therefore, two natural groups, an attractive group of 41 firms and a non-attractive group of 35 firms, could be used for a basic discriminant analysis input (four firms did not align with either factor).

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[1] W. J. Dixon and F. J. Massey, Jr. Introduction to Statistical Analysis. New York: McGraw-Hill Book Company (1969), 240-243.

TABLE 4.7

NEW CLASSIFICATION OF OBSERVED GROUPS

Actual Observed Grouping	New Groupings by Factor Load		
	Factor 1	Factor 2	
NON-ACQ	15	22	37
ACQ	26	13	39
	41	35	76*

$X^2 = 4.24$

$X_{.05}(1) = 3.84$

*4 firms from the original sample failed to align with either factor.

DISCRIMINANT ANALYSIS WITH NATURAL GROUPS

A second discriminant analysis was performed with the difference being that the observed samples were replaced by the natural samples. For the purpose of direct comparison with the first discriminant model, the same four variables were employed to generate the following discriminant function

$$Z = .531X_1 - .573X_2 + .082X_3 - .619X_4$$

where again

X_1--net income/total assets

X_2--sales/total assets

X_3--net working capital/sales

X_4--long term liabilities/total assets

Table 4.8 is analogous to Table 4.1 for the first model in that it presents the group means for each of the ratios as well as a univariate F-test for group differences for each of the ratios. Table 4.8 gives considerable insight as to how the factor analysis re-aligned the 80 firms into two groups of attractive and non-attractive firms. In Table 4.8 the attractive group is group 1 and firms in group 1 are significantly different from those in group 2 on three of the four variables. For the tests of the observed samples, only ratio 4, the leverage variable, was significantly different between the groups.

The importance of the results of the test presented in Table 4.7 is now apparent. Table 4.7 presented the new classification of firms based upon attractiveness, and this was tested to see of the alignment of the majority of the acquired firms to the first factor, and the majority of the non-acquired firms to the second factor, could have been attributed to chance. The chance hypothesis was rejected at the .05 level. The hypothesis accepted therefore was that attractiveness and acquisition aligned, and that non-attractiveness and non-acquisition aligned. That hypothesis was further explored in the ensuing analysis.

From Table 4.8 it can be concluded that attractive firms were more profitable, more liquid, and had lower

TABLE 4.8

UNIVARIATE TESTS OF SIGNIFICANCE FOR GROUP MEANS: NATURAL GROUPS

Variable	Ratio	Group Means 1 ATTRACTIVE	Group Means 2 NON-ATT	F
X_1	net income/assets	7.18	3.94	10.43*
X_2	sales/assets	1.40	1.38	.02
X_3	NWC/sales	36.46	23.58	10.38*
X_4	LT liabilities/assets	9.53	28.44	68.69**
		n=41	n=35	

**F (1,60)(.001) = 11.97

*F (1,60)(.005) = 8.49

levels of financial leverage. With respect to the turnover of assets there appeared to be no difference between the samples. This set of conclusions drawn upon the series of univariate tests, cannot be generalized to the joint effect of these four variables upon the samples.

Table 4.9 represents the differences between the groups in a multivariate context as measured by the distance between the two centroids. The F was significant at the .001 level indicating the degree of separation between the groups in four-space. Given the significance of three of the four variables on a univariate basis, the analysis of the relative contribution to total discrimination of the

TABLE 4.9

MDA: GROUP DIFFERENCES, NATURAL GROUPS

Group Centroids		
1	Attractive	.099
2	Non-Attractive	-14.368
	Wilks lambda	.485
	F(4,72) =	19.88
	F(4,60)(.001) =	5.31

four variables in a multivariate context was important. The scaled vectors and the corresponding rank is listed in Table 4.10. Once again the leverage variable dominated the space indicating that the degree of leverage for a firm is an important determinant of difference between the two groups. Although almost equally significant in a univariate measure, the profitability variable was a larger factor than the liquidity factor in the multivariate context, and both of these were much larger than the activity factor.

In addition to the comparison of group separation between the two groupings--observed and natural--which formed the basis for the discriminant analyses, a second significant comparison was made. That was the ability of

TABLE 4.10

MDA: SCALED VECTORS AND DISCRIMINANT FUNCTION, NATURAL GROUPS

Variable	Ratio	Discriminant Coefficient	Scaled Vector	Rank
X_1	net income/assets	.53	20.96	2
X_2	sales/assets	-.57	-3.02	4
X_3	NWC/sales	.08	12.83	3
X_4	LT liabilities/assets	-.62	-55.49	1

the discriminant function to classify the firms accurately into the proper groups. The results of the classification are in Table 4.11. The ability of the reformulated model using the naturally defined groups was a noticeable improvement over the first model using observed groups. In the first model, using observed groups, the discriminant function resulted in classification with 65% accuracy. As shown in Table 4.11 the overall classification was 90% accurate with only 9 firms mis-classified from the sample of 76. This was to be expected because the increased distance between the group centroids implied that the overlap between the distribution of firms around the centroids would be less than if the centroids were relatively close.

TABLE 4.11

MDA: CLASSIFICATION MATRIX, NATURAL GROUPS

Actual	Predicted ATTRACTIVE (%)	#	NON-ATTRACTIVE (%)	#	
ATTRACTIVE	(95)	39	(5)	2	41
NON-ATTRACTIVE	(23)	8	(77)	27	35
		47		29	76
$t = 6.5$					% correct 87
$t_{(60)}(.005) = 2.58$					

However, the reformulated model represented a model constructed from the variables which had been most representative of the first analysis using observed groupings of firms. That in no way implied that other variables would not better discriminate in the reformulated model using natural groups. From the standpoint of attractiveness, certain variables could become important where they were of no benefit in the first analysis. Therefore, a new series of tests and computer runs were performed to measure the effect of the introduction of variables measuring price-earnings, dividend payout, and alternative ratios measuring profitability, leverage, liquidity, and activity. The variables retained in the final discriminant function were

those which performed best in the multivariate context. However, all combinations of all variables were not tested, and to that extent, no claim can be made with respect to the optimality of the final discriminant function

$$Z = .052X_1 + .163X_2 + .079X_3 - .953X_4 - .236X_5$$

where

X_1--DIVIDEND PAYOUT RATIO. This ratio measured the percentage of earnings which were distributed to the owners in the form of cash dividends. The hypothesis has been advanced that if firms have low payout ratios, their stockholders tend to become dis-satisfied and are more willing to agree to a merger. This would imply that acquired firms would have lower dividend payout ratios than non-acquired firms and thus attractiveness and low dividend payout would coincide.

X_2--NET INCOME/TOTAL ASSETS. This measure of profitability was the same as that used in the first model.

X_3--NET WORKING CAPITAL/TOTAL ASSETS. This measure of liquidity was similar to that employed in the first model with the exception of the denominator changing from sales to total assets. The same relationships remain, however, with respect to the comparison of the samples. The higher the level of liquidity, the more attractive the firm.

X_4--SALES/TOTAL ASSETS. This measure of efficiency in the

employment of assets was the same variable as was used in the first analysis.

X_5--LONG TERM DEBT/TOTAL ASSETS. This ratio was altered in the numerator from the ratio used in the original model. In this context long term debt was differentiated from long term liabilities in the following manner. The only items included in long term debt were actual long term debt instruments such as bonds and notes. Long term liabilities included in addition, various accounting entries such as deferred compensation, deferred taxes, etc. The distinction was made with the logic that perhaps the same distinction is made in the market place and a firm's capital structure is valued differently with respect to different long term entries. The basic relationship remained the same, however, in that the attractive firms were expected to have lower levels of borrowing.

Table 4.12 is a comparison of the group mean differences on a univariate basis and is comparable to both Tables 4.1 and 4.8. The attractive firms were significantly more profitable, more liquid, and had lower financial leverage and higher dividend payout. Note that the dividend payout variable entered the function at a level of significance second only to the leverage variable which consistently dominated all of the models. It was also interesting to

TABLE 4.12

SIGNIFICANCE FOR GROUP MEANS FOR NATURAL GROUPS AND REFORMULATED MODEL

Variable	Ratio	Group Means 1 ATTRACTIVE	Group Means 2 NON-ATT	F
X_1	dividend payout	46.7	25.4	15.3**
X_2	net income/assets	7.3	3.8	11.8*
X_3	NWC/assets	44.2	32.4	11.7*
X_4	sales/assets	1.42	1.40	.01
X_5	LT debt/assets	7.6	25.0	68.8**
		n=41	n=35	

**F(1,60)(.001) = 11.97

*F(1,60)(.005) = 8.49

note that attractive firms were also the firms with the higher dividend payout ratios, which would contradict the stockholder dis-satisfaction hypothesis.

Table 4.13 contains the test of the group differences with respect to their centroids and the F was very significant at the .001 level. In comparison with the grouping of firms by observed groups, where the F was only significantly at the .10 level, the natural group formulation is even more convincing. The chance that the natural group formulated from the factor analysis could have come from the same population was less than one in one thousand.

TABLE 4.13

MDA: GROUP DIFFERENCES, REFORMULATED MODEL

Group	Centroids		
1	Attractive		3.969
2	Non-Attractive		2.740
		Wilks lambda	.373
		F(5,70) =	23.56
		F(5,60)(.001) =	4.76

Table 4.14, which measures the scaled vectors, or the relative contribution to total discrimination for each variable, again points out the significance of the leverage variable. But the appearance of the dividend variable as the second most important of the five variables, indicated that its presence added to the ability of the model to discriminate between groups.

A most important test of the model was the classification accuracy, which Table 4.15 indicates was 92% for the 76 firms. The significant t-test substantiated that the classification was not due to chance. An illustration of the classification results is in Table 4.16 where the actual Z-scores were listed. Each firm was assigned a Z-score by adding the products of the individual X_1, X_2, X_3, X_4, and X_5

TABLE 4.14

MDA: SCALED VECTORS AND DISCRIMINANT FUNCTION, REFORMULATED MODEL

Variable	Ratio	Discriminant Coefficient	Scaled Vector	Rank
X_1	dividend payout	.052	10.49	2
X_2	net income/assets	.163	6.22	4
X_3	NWC/sales	.079	10.26	3
X_4	sales/assets	-.953	-4.50	5
X_5	LT debt/assets	-.236	-18.54	1

TABLE 4.15

MDA: CLASSIFICATION MATRIX, REFORMULATED MODEL

	Predicted				
Actual	ATTRACTIVE		NON-ATTRACTIVE		
	(%)	#	(%)	#	
ATTRACTIVE	(95)	39	(5)	2	41
NON-ATTRACTIVE	(13)	4	(87)	31	35
		43		33	76
t = 7.3					% correct
t(60)(.005) = 2.58					

TABLE 4.16

INDIVIDUAL FIRM DISCRIMINANT SCORES

$$Z = .052X_1 + .163X_2 + .079X_3 - .953X_4 - .236X_5$$

Group 2 (Non-Attractive) Ranked Z-Scores		Group 1 (Attractive) Ranked Z-Scores	
n=35		n=41	
Firm No.	Z-Score	Firm No.	Z-Score
17	-9.25	1	8.12
18	-7.70	8	8.00
8	-7.29	15	7.26
32	-6.98	7	7.25
34	-6.30	11	6.99
20	-5.81	25	6.91
13	-5.63	19	6.74
10	-5.29	40	6.50
3	-5.03	24	6.38
11	-4.84	30	6.32
5	-4.30	17	6.18
21	-4.23	18	5.80
22	-4.22	27	5.31
16	-4.12	26	5.15
9	-3.86	6	5.09
15	-2.99	13	4.66
35	-2.59	39	4.55
23	-2.48	21	4.41
25	-2.26	10	4.12
33	-2.15	38	4.05
27	-1.77	32	4.02
4	-1.59	29	3.98
19	-1.49	20	3.85
19	-1.46	9	3.67
2	-1.25	2	3.51
26	-0.23	37	2.75
31	-0.21	23	2.49
7	0.14	16	2.47
12	0.18	22	2.18
24	0.20	5	1.97
30	0.25	14	1.87
14	0.45	28	1.73
1	0.75	3	1.58
28	1.14*	34	1.50
12	1.84*	36	1.25
		12	1.21
		35	1.01
		41	0.87*
		31	0.86*
		33	0.27*
		4	-0.13*

Group 1 centroid: 3.97
Group 2 centroid: -2.74

$Z_{critical} = 0.89$

*misclassified by model

variable values and the corresponding discriminant coefficients for each of the X's. The $Z_{critical}$ was the sum of the individual products of the grand means for each variable and the corresponding discriminant coefficients. In the illustration, each firm's score was listed in the table and indicated by the number of the firm with respect to its group. The group centroids were listed to locate the center of each group's distribution of scores. With respect to the $Z_{critical}$, the six mis-classified firms can be observed easily in that the firm numbers were noted in each case with an asterisk.

VALIDATION OF RESULTS

Morrison noted that studies of the type which would include this one must consider bias introduced due to the programming method and subsequent testing of the discriminant model.[1] Specifically, if the program uses all n observations to calculate the discriminant function and then classifies these same n individuals with this function, the result is an upward bias that is reflected in the classification tables. One method of avoiding this bias is to fit a discriminant function to part of the data and then use this function to classify the remaining individuals.[2]

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[1]Morrison, op. cit., 160-162.

[2]Morrison, op. cit., 160-162.

This possibility was explored with respect to the reformulated model. The two a priori groups were divided randomly and a discriminant function was developed using half of each of the groups. Then the remaining firms were classified using the function developed by the first half sample. The results supported the validity of the initial results as shown by Table 4.17. A total of 36 of the 39 firms in the split sample were correctly classified, which was the same level of accuracy achieved by the testing of the entire sample. Thus, the model demonstrated an ability to achieve the same results with firms not used in the development of the discriminant function.

TABLE 4.17

MDA: CLASSIFICATION MATRIX FROM VALIDATION OF MODEL

	Predicted				
Actual	ATTRACTIVE		NON-ATTRACTIVE		Total
	(%)	#	(%)	#	
ATTRACTIVE	(90)	19	(10)	2	21
NON-ATTRACTIVE	(5)	1	(95)	17	18
					39
t = 5.25					% correct
t(40)(.005) = 2.704					92

SUMMARY

In summary, when the observed groups are reformulated such that an attractiveness criterion determined group membership, the resultant discriminant function was able to classify the firms with an accuracy of over 90%. Furthermore, a validation test of the results, using firms for classification which were not used to develop the discriminant function, indicated that the accuracy of 90% was maintained.

The variables used to develop the discriminant function were such that firms aligned into significantly different groups with respect to four of the five variables on a univariate basis. With the multivariate framework the five variables jointly were able to divide the groups at a distance which allowed rejection of the null hypothesis of no difference between the groups at the .001 level.

The significance of the group differences, and the consistent behavior of the firms within their respective groups, on all of the variables, allowed the following observations. The majority of the firms actually acquired, and the attractive firms in general, were those who were more profitable, more liquid, paid higher cash dividends relative to their earnings, and had lower levels of long term debt outstanding relative to their assets.

CHAPTER V

CONCLUSIONS, EVALUATION, LIMITATIONS AND SUGGESTIONS FOR FUTURE RESEARCH

INTRODUCTION

This chapter is divided into five parts. First the hypotheses of chapter two are individually examined and conclusions drawn about financial characteristics which make a firm attractive for acquisition. Second, the quantitative framework is evaluated as to its usefulness in this research context and for its potential use in other related research in finance. Third, the limitations of the study are discussed. Assumptions, both stated and implied are examined in light of the results. Given the restrictions imposed by the limitations, a general application of the discriminant model for the decision makers in merger oriented firms is illustrated. Finally, general conclusions and suggestions for future inquiry are summarized.

FINANCIAL CHARACTERISTICS

The hypotheses developed in Chapter II can now be examined in light of the test results and in the context of attractiveness for acquisition. Briefly stated, Chapter II

concluded by predicting that acquired firms would be more liquid, have lower levels of debt, and lower price/earnings ratios. No predictions in a univariate sense, were made about dividend policy and profitability. The implied null hypotheses, in each case, were that the two samples would show no significant differences on any of the variables, independently or jointly.

Significant differences were found, in a series of univariate tests, between attractive and non-attractive firms, for the variables measuring liquidity, profitability, leverage and dividend policy. The activity variable was part of the multivariate test function which was itself significant, but the univariate test indicated the null hypothesis could not be rejected. The price/earnings ratio variable was not significantly different in the univariate test and that variable failed to enter the discriminant model altogether, indicating that it did not assist in discriminating between the samples.

With respect to the variables which were significant in univariate tests, all were of a level of significance such that occurrence could be attributed to chance only five times in 1000. With respect to the multivariate test of differences between the samples based on the five variables--liquidity, leverage, profitability, activity,

and dividend policy--the level of significance was well beyond the .001 level. Thus, these variables produced very different profiles between the two samples.

Given these high levels of statistical significance, the following observations can be made: Firms which are attractive as merger targets are more profitable, have higher levels of liquidity, lower levels of debt, and higher dividend payout ratios. These factors jointly and systematically differentiate them from their non-attractive, non-acquired counterparts.

These results would be consistent with the Alberts-Manne mis-management bargain hypothesis. That is, conservatively managed firms who tend to minimize aggressiveness are carrying higher levels of liquid assets and avoiding borrowing to the extent that they have considerable unused debt capacity. The more than adequate liquidity and profits allow the payment of higher dividends.

The acquisition of these firms serves the acquiring firm with several opportunities. First, aggressive employment of assets to minimize excess liquidity will free cash for use in other areas of the combined firm. The profitability of this type of firm will help assure the maintenance of a good earnings picture for the combined firm. The unused debt capacity will provide a large source of

funds for the merged firm when added to the increment which accrues due to the increase in absolute size from the merger.

This last point, as well as the dominance of the leverage variable for all phases of the analysis, confirms the financial rationale argument of Lewellen and Lintner. This variable alone discriminated significantly between the samples at very high levels of significance. No other variable was as significant in a univariate test and the leverage factor was the largest single contributor to group discrimination in the multivariate model. Lewellen argued that both firms could have optimal capital structures and still benefit in added debt capacity. However, this analysis indicated that unused debt capacity itself was very important and that an optimal capital structure was not often found in the attractive sample.

Finally, the usefulness of the financial criterion approach itself was confirmed. It was argued in Chapter II that although a myriad of specific reasons could be found for why a merger could occur, there would be merit to identifying a framework which could assimilate these diverse reasons and discover some degree of communality among them. It was proposed that all decisions to expand are evaluated for their financial benefits and a capital budgeting framework was proposed. Therefore, regardless of

the reasons stated for acquisition--marketing, production, or other operating benefits--these benefits would be reflected in the financial variables of the firm. If this were the case, and these common characteristics were systematically different and could be detected in the financial variables of the firm, this approach would be successful.

The approach was validated by the results. This does not exclude the possibility that numerous acquisitions were made for other than financial reasons. Nor does this approach deny the existence of numerous mergers which take place for completely unrelated reasons which would be undetectable in the financial characteristics of the firm. The existence of several acquired companies in the non-attractive sample was testimony to these points. However, this approach was able to find several qualities which allowed accurate classification of firms according to these qualities which supports the argument that differences exist and indicates which variables differed between the samples.

MULTIVARIATE FRAMEWORK

A second purpose of this research was to explore the applicability of a multivariate framework in the financial analysis context. Factor analysis was used in two different ways and discriminant analysis was used directly to develop the model. It was noted that regression analysis dominated

research in finance when multivariate techniques were employed. The over-reliance upon regression was seen as a limitation in certain areas of development in finance.

The results of the research confirm the usefulness of the multivariate framework. Variables which were not significant in a univariate context provided important discriminating ability in the multivariate model. The multivariate analysis considered the combined effects of the variables and allowed conclusions to be drawn on the firm profiles measured by several variables. The significance of the combined effects can be seen from the univariate tests and the discriminant function in the first "observed" model. In that case, only leverage was different between the samples for the univariate tests. However, four variables combined to achieve significant discrimination at the .10 level, in the multivariate discriminant function. This finding also occurred in Altman's study of bankruptcy using MDA. Beaver,[1] in an earlier study of bankruptcy using only univariate tests, had found single ratios which were good predictors of failure, but the Altman model was able to consider several variables simultaneously and allowed

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[1]Beaver, William. "Financial Ratios as Predictors of Failure," Empirical Research in Accounting: Selected Studies 1966, Supplement to Volume 4, Journal of Accounting Research (1966) 71-122.

considerably greater insight. Therefore, the added information of the multivariate framework demonstrated by this and other recent studies, should provide incentive to future related research.

FACTOR ANALYSIS FOR DATA SIMPLIFICATION

The use of factor analysis in this study for the purpose of simplifying the original data allowed the use of an analytical tool where more heuristic and judgemental bases were traditionally used. In both similar studies using MDA, by Altman in bankruptcy, and Monroe and Simkowitz in mergers, the movement from a large number of "potentially helpful" initially chosen ratios, to the several retained in the final discriminant function, depended on a great number of computer runs to test some of the combinations of ratios available. Also, when techniques such as these, and stepwise techniques, are used, if the data set contains independent variables which are highly correlated among themselves, the results are unstable and often hard to interpret. This problem exists with any multivariate technique if multi-collinearity is present, and according to Morrison,[1] using factor analysis as in Chapter III, can minimize this problem. In that the factor analysis aligned the original

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[1]Morrison, op. cit., 160.

variables on a small number of uncorrelated factors, the original space was simplified with little loss of information. This was possible because of the high inter-correlations of the data. Financial ratios by their very nature are often highly correlated and therefore extremely susceptible to this technique of data simplification. Once the independent factors are established in the reduced space, the highest loading ratio from each factor can be chosen to represent that factor. If the loading of ratio x on factor p is close to 1.0, for example, ratio x will offer nearly complete description of factor p, even if factor p also contains other ratios with high loadings. There is no need to retain these others for further analysis as they add nothing "new" that isn't provided by the chosen ratio for that factor. In general, when variables are selected from each factor due to their high loadings and when factors are orthogonal, the ratios themselves will be uncorrelated. Such was the case in this study among the five ratios retained in the final discriminant function. Table 5.1 indicates that only one simple correlation between variables three and four, was even moderately high.

One important addition is necessary here with respect to the use of factor analysis prior to discriminant analysis. Factor analysis is one of a class of techniques of analysis

TABLE 5.1

CORRELATION MATRIX FOR VARIABLE IN REFORMULATED MODEL

	X_1	X_2	X_3	X_4	X_5
X_1	1.00				
X_2	.17	1.00			
X_3	.04	.20	1.00		
X_4	.00	.00	.30	1.00	
X_5	-.24	-.25	-.22	-.07	1.00

of inter-dependence. Thus, no dependent variable exists. Therefore, factors are achieved by maximizing the reduction of total variance within the entire set, not between any groups within the entire set. Those factors most significant in variance reduction allow no further insight as to which variables may best discriminate between the groups. When the MDA is performed, being part of analysis of dependence, it has a dependent variable. The analysis determines which set of independent variables best discriminates between groups. The factor analysis helps choose the independent variables from a large set and minimize their inter-correlations. It is therefore important that all significant factors be retained from the factor

analysis and that MDA be the determinant of which of the independent variables is finally retained.

MDA & RE-EVALUATION WITH FACTOR ANALYSIS

As was stated initially, the use of MDA is not new in finance. Although still not widely used, it is found increasingly greater application in the finance literature. Its use in this study was a further extension of past application, in a new context. Also, the explicit evaluation of some basic assumptions of the model (multi-collinearity among independent variables and mutually exclusive groups) was not apparent in earlier studies. The importance of the natural group assumption resulted in a reformulation of the approach of the study and the significance of the results testified to the importance of evaluating these requisites.

The ability of the final discriminant model to accurately classify firms not used in the development of the model was demonstrated. Classification accuracy for the holdout sample was over 90%, and validated the similar results for the original sample. Therefore, it appears that, once again, the power of multivariate analysis justifies its consideration in applications other than regression, and wherever simultaneous consideration of several variables is needed.

The use of factor analysis to re-structure the

original sample of 80 firms proved to be successful in its goal of arriving at "natural" and mutually exclusive groups. This was noted to have been used in marketing but not seen often in finance. The results, two factors accounted for 82% of total variance, and "consumed" 76 of the 80 firms, were rather surprising when the total set of a priori outcomes is considered. The question posed by this approach to factor analysis was this: Given twenty financial ratios, how many different types of firms are there among the 80 firms? The emergence of only two basic types (76/80 firms) raises interesting questions for future examination. For example, would two factors do as well with other samples stratified by size, industry, etc., or in other contexts such as growth versus non-growth firms?

The first factor analysis suggested that any initial number of financial ratios can probably be reduced to a much smaller set because there are only a small number of actual qualities (dimensions) describable by financial variables. The second factor analysis raised questions as to the possibility of a small set of firm types with respect to financial variables. Additional investigation into this area would appear to have merit.

ASSUMPTIONS AND LIMITATIONS

Sampling error must always be evaluated in order to put test results in proper perspective. In this study, all firms were large in that $10 million asset cutoff was used. Data availability is sparse for smaller firms and it is difficult to evaluate potential differences between small and large firms on the test variables. Bias will exist in the sample to the extent that there are differences in these size strata. Also, the existence of reasons for acquisition unrelated to any measurable financial variable has lessened the ability of the model to predict or classify for all firms. An assumption of any application of this model must be that financial characteristics were relevant decision variables, or that they reflected systematically, the relevant decision variables.

There is always a certain amount on non-sampling error, primarily due to the data. The data was secondary at the outset, and hence, subject to possible errors in recording by the firm itself, Moody's, and at the time of data collection and transformation. Also, the occurrence of extreme values for any of the variables could influence the results. Although careful screening was performed to identify and verify extreme observations, their presence can often change the appearance of the aggregated data.

In this study, two explicit attempts were made to minimize potential bias of this type. First, a screen was run and all observations greater than three standard deviations from the group means were identified. Then, ratios which were consistently including extreme values were eliminated and new measures of the same financial quality were substituted. Often the extreme values resulted in complete distortion of the financial quality under investigation. For example, one firm had current ratios of 190:1, which, by itself would imply an extreme level of liquidity. But when net working capital was measured in relation to assets for the same firm, it was less than ten per cent. Therefore, for this firm, it was the current asset-current liability relationship which was extreme, not the liquidity relationship. Thus, the net working capital/assets ratio was much more meaningful for use in the analysis. To further limit the potential bias introduced by extreme values, the raw data for the final analysis represented the average value of the two most recent test years, 1965 and 1964, for each ratio. This further lowered the possibility that one extreme value would unduly influence the results.

The assumptions of the MDA model should also be discussed and conclusions made must be drawn with regard to any violations of these assumptions. The problems caused

by highly correlated independent variables and poorly defined a priori groups, have already been evaluated. However, another basic assumption is that the observations on the groups are jointly normal with equal variance-covariance matrices. This assumption, which is standard in most statistical models with inference as a goal, is not often met by social scientists, especially when economic or financial data is used. Furthermore, most published research does not directly evaluate either of these assumptions or the consequences of the violation of the assumptions. Rather, it is generally recognized that true statistical inference from most studies of this type is limited. The ability of one sample to have conclusions which can be generalized to the population does depend upon meeting all assumptions. In that normality and homogeneity of dispersions requirements are not met, ability to make inferences does not exist from a single study. In that inference is seldom made from one study, great reliance is placed upon repetition and replication where promise has been demonstrated.

Such was the case in this study; MDA assumptions of normality and homogeneity of dispersions could not be rigorously upheld. However, with respect to this particular tool, Cooley and Lohnes have pointed out that researchers frequently bypass formal tests for these assumptions in

that for moderate departures from the assumptions, the hypothesis is rather insensitive.[1]

Nonetheless, departures from assumptions in multivariate analysis as well as the sampling and non-sampling error which was inherent in the research, should be identified and considered when drawing conclusions. This would be particularly true if significance levels of the test results were only marginally significant in rejecting the null hypothesis. The high levels of significance for this study remain encouraging, however, even when the limitations are considered. Certainly future extension and replication will add insight into presence of bias and to the population stability of the model.

APPLICATION AND SUGGESTIONS FOR FUTURE RESEARCH

A model such as this could be useful to both an acquisition minded firm and any manager interested in measuring his firm's relative attractiveness as an acquisition candidate. For the merger active firm, the present model could be directly used with the five attractiveness variables used to develop an overall profile on each of a number of relevant groups. For instance, all of the firm's past acquisitions and/or past acquisition targets which were not

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[1]Cooley, W. W. and Lohnes, P. R. Multivariate Procedures for the Behavioral Sciences, New York: John Wiley & Sons, Inc. (1962) 61.

subsequently acquired could be given a Z-score to see how they would have been rated by the model. This could provide a basis for the reformulation of the present model into a more specific model oriented only to the goals of that firm. This could be used as a screening device in that it is extremely simple and inexpensive to use once the model is developed. All that is needed from potential firms would be several financial variables.

With respect to firms in general who are interested in their own attractiveness, they would simply compute their firm Z-score directly by the sum of the products of each of their own five variable scores and each respective discriminant coefficient. In this context, the same opportunity would be available to the stockholders and competitors of any publicly held company.

A number of questions have been raised by this study which merit future inquiry. First, general replication of this study, perhaps introducing new variables or additional financial quantities, appears justified. Also, other time periods should be evaluated to give insight as to if "attractiveness" appears to have different definitions at different points in time.

Second, wherever data is available, this study could be extended to small firms which were excluded from this

study. Here it would be interesting to see if the same criteria were applied to these companies. Perhaps the cost-of-capital bargain hypothesis summarized by Alberts and related criterion variables such as price/earnings ratio would find a significant place in the discriminant function.

Third, alternative sample designs would provide less general but more detailed knowledge. Samples could be drawn using matched pairs of firms by industry and size. Thus, acquired and non-acquired firms of the same size and from the same industry could be directly compared. Both Beaver and Atlmen employed this technique in their bankruptcy studies. Another type of stratification would be by type of merger. The conglomerate merger has dominated the last decade and the type of merger could be compared with differing profiles of attractiveness. This would be an avenue to test the numerous hypotheses pertaining to conglomerate motives.

The attractiveness-non-attractiveness criterion could be used for an ex-post study of "bad" merger decisions. A large number of spin-offs and divestitures have been reported during the last several years. These firms which were once acquired and then sold, could be evaluated as a group. Their pre-merger financial characteristics could be analyzed to see if they would have been attractive or

unattractive at the time of acquisition, according to the model.

Another general area of inquiry which merits future work is the use of the factor analysis and discriminant analysis techniques. Factor analysis particularly has not seen many applications in published research in finance. Its potential as a data simplification tool, and as a tool to identify structure in data was further advanced by the results of this analysis. Perhaps this will encourage others to consider the set of multivariate techniques when designing a project, rather than modifying the project to fit the regression model.

APPENDIX I

FACTOR ANALYSIS

The intent of the following section was to provide a more rigorous development of factor analysis using the standard statistical notation. This is a standard development and benefited from both Harman, and the Sheth and Tigert paper. A more rigorous treatment can be found in Harman.

FACTOR ANALYSIS

The starting point for any statistical method is the observed data matrix. The correlation matrix is a transformation of the original data matrix which standardizes the data by setting the mean equal to zero and the variance equal to one. Thus, both the level and the scatter of the data are lost. The standard factor analytic procedures begin with the correlation matrix.

Factor analysis simplifies a data matrix by summarizing each variable's variance in a small number of factors. Each of the variables is linearly dependent upon these factors which are themselves composed of common factors and unique factors.

Therefore,

$$x_{ji} \sim \hat{x}_{ji} = a_{j1}F_{1i} + a_{j2}F_{2i} + \ldots + a_{jr}F_{ri} = \sum_{m=1}^{r} a_{jm}F_{mi} \qquad (1)$$

and, in matrix notation

$$X \sim \hat{X} = AF \tag{2}$$

In the case of common and unique factors, the following applies

$$Z_j = a_{j1}F_1 + a_{j1}F_2 + \ldots + a_{jr}F_r + d_jU_j \tag{3}$$

or,

$$Z_j = \sum_{m=1}^{r} a_{jm}F_m + d_jU_j$$

The total variance of a variable Z_j (in standard scores) is summarized by a set of common factors (F_m) and by a unique factor (U_j). That portion of a variable's variance which co-varies with other variables in the data is classified among the common factors and the balance is retained in the unique factor.

The total variance of a variable j is simply the average of squared standard scores of a sample of N observations.

Then, based on equation (3)

$$S_j^2 = \Sigma Z_{ji}^2/N = \sum_{m=1}^{r} a_{jm}^2 (\Sigma F_{mi}^2/N) + d_j^2 \Sigma U_{ji}^2/N \tag{4}$$

$$+ 2 \sum_{m<p=1}^{r} a_{jm}a_{jp}(\Sigma F_{mi}F_{pi}/N) + 2d_j \sum_{m=1}^{r} a_{jm}(\Sigma F_{mi}U_{ji}/N)$$

In the above equation, it is assumed that all the variables, including factors, are in standard form. Then

$$S_j^2 = 1 = \sum_{m=1}^{r} a_{jm}^2 + d_j^2 + 2 \sum_{m<p=1}^{r} a_{jm}a_{jp}r_{FmFp} + 2d_j \sum_{m=1}^{r} a_{jm}r_{FmUj} \tag{5}$$

The last term in (5) is zero because the unique factor (U_j) and the common factors are uncorrelated ($r_{FmUj} = 0$). In an orthogonal representation of the space, the common factors are also uncorrelated among themselves ($r_{FmFp} = 0$, $m \neq p$) and the middle term in (5) equals zero. The simplified expression,

$$S_j^2 = 1 = \sum_{m=1}^{r} a_{jm}^2 + d_j^2 = a_{j1}^2 + a_{j2}^2 + \ldots + a_{jr}^2 + d_j^2 \qquad (6)$$

It will be seen that each a_{jm}^2 represents a portion of total variance in Z_j which is summarized in factor F_m. In a similar manner, the same factor F_m will summarize part of the variances of other variables. The total contribution of common factors toward summarizing the variance of Z_j is called h_j^2, and this equals

$$h_j^2 = \sum_{m=1}^{r} a_{jm}^2 = a_{j1}^2 + a_{j2}^2 + \ldots + a_{jr}^2 \qquad (7)$$

This is referred to as the communality of Z_j, and represents the portion of total variance in Z_j that is common to the other variables. If the data are orthogonal and is standard form, each factor loading (a_{jm}) represents a product-moment correlation between the variable j and factor F_m. In this case Σa_{jm}^2 represents a squared multiple R in the regression sense. Therefore, each h_j^2 can be thought of as a squared multiple R between a variable j and the common factors. The total communality, h_j^2, of all the variables in a data matrix

is then

$$h^2 = \sum_{j=1}^{n} h_j^2 = \sum_{j=1}^{n} \left(\sum_{m=1}^{r} a_{jm}^2 \right) \tag{8}$$

The unique variance (d_j^2) of a variable Z_j is ($1-h_j^2$). However, this variance itself can be thought of as consisting of two components: stable variance (true variance) and error variance.

$$1 - h_j^2 = d_j^2 = g_j^2 + e_j^2 \tag{9}$$

where g_j^2 is the true unique variance and e_j^2 is error variance. Therefore, with respect to the total variance of a variable, S_j^2

$$S_j^2 = 1 = h_j^2 + g_j^2 + e_j^2 = \sum_{m=1}^{r} a_m^2 + d_j^2$$

Having shown that the total variance of a variable is summarized in a set of common factors and a unique factor, equation (3) may be written for all of the n variables as follows:

$$\begin{aligned} Z_1 &= a_{11}F_1 + a_{12}F_2 + \ldots + a_{1r}F_r + d_1U_1 \\ Z_2 &= a_{21}F_1 + a_{22}F_2 + \ldots + a_{2r}F_r + d_2U_2 \\ Z_n &= a_{n1}F_1 + a_{n2}F_2 + \ldots + a_{nr}F_r + d_nU_n \end{aligned} \tag{10}$$

Thus, a data system of n variables is summarized in r common factors and n unique factors, or a total of

$(r + n) > n$, which seems contradictory to the principle of parsimony which underlies factor analysis. This apparent contradiction arises from the assumption that the communality equals the total variance of a variable (unity). The unique factors are not derived from the resolution of the data matrix, but are calculated as residuals to account for the difference between communality and unity. Alternatives exist to either include total variance of the variables in factor analysis, or only that part of it which represents communality. If total variance is explicitly included in the factor analysis, this assumes total variance will include the unique portion and the total will be approximated by the factor matrix. In this case, the model is as follows:

$$Z_j = a_{j1}F_1 + a_{j2}F_2 + \ldots + a_{jr}F_r \qquad (11)$$

and $S_j^2 = \sum_{m=1}^{r} a_{jm}^2$

This solution is known as principal components analysis and was the method employed in this study. The latter solution, including only that portion which represents communality, is known as classical factor analysis. Harman has noted that the principal components solution is that generally employed is empirical research.

If the classical solution is desired, then the common factors will approximately reproduce the communality of

the variable ($h_j^2 < 1$), and a unique factor will be necessitated to account for total variance.

While the two models, as expressed by equations (3) and (11), are distinctly different, the procedures are essentially the same in the derivation of factor loadings and factor scores matrices. The only difference is that while total variance ($S_j^2 = 1$) is retained in principal components analysis, an estimate of communality is substituted for total variance ($S_j^2 = h_j^2$) in the data matrix before factoring in classical factor analysis.

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